A higher-order life crafting scale validation using PLS-CCA: the Italian version

Published version:

DOI:10.1007/s41237-023-00209-y

Behaviormetrika manuscript No.
(will be inserted by the editor)

A Higher Order Life Crafting Scale validation using Confirmatory Composite Analysis: the Italian version.

First Author · **Second Author**

Received: date / Accepted: date

Abstract Using the Partial Least Squares Structural Equations (PLS-SEM) model, Life Crafting Scale (LCS) factor structure and model specifications were highlighted in this study using Confirmatory Composite Analysis (CCA) with a sample of students Italians (n=953). From the validation results obtained through CCA emerges both the reflective nature of the scores of the LCS subscale and an alternative measurement model of the LCS scores as a second order reflective-reflective model.

Keywords Confirmatory Composite Analysis · Partial Least Square · Structural Equation Modeling · Life Crafting

Mathematics Subject Classification (2020) MSC code1 · MSC code2 · more

1 Introduction

The current post-pandemic context is characterized by deep uncertainty, from different perspectives: economic, social and even generational. Not only the pandemic, but also the persistent economic crisis that had surfaced in the pre-pandemic period, have generated and increased in people a sense of precariousness that everyone has subjectively experienced in their personal life, which has had important repercussions on their self and working frameworks. In last years, events affecting the planet have changed the way we live, leaving us without reference points. These challenges individuals of all ages. Just to give one example, the COVID-19 pandemic has had severe consequences for the mental health of individuals, causing a general worldwide concern about the rising suicide rate. For the first time, mental health surpasses cancer

F. Author
first address
Tel.: +123-45-678910
Fax: +123-45-678910
E-mail: fauthor@example.com

S. Author
second address

to become the second-largest perceived health problem internationally, just behind COVID-19. 55 percent of Italians say they often think about their mental well-being, up 4 points from 2021 (Chambers et al., 2022). This situation carries psychological costs not only for healthcare workers and people with COVID-19 but also for the general population. According to researchers, the emotions experienced in this situation are very similar to those of bereavement, and people experience emptiness and sadness over the loss of their normal life, which can even lead to a loss of meaning in life (Fegert et al., 2020). In addition, there has been such a high suicide rate among very young students at Italian universities recently that it has set off alarm bells in Italy. At least three suicides occurred among college students in 2022. Also weighing on their choice was the perceived inadequacy in the stages that mark the course of study. Two more in a single month in 2023. Recent studies have shown that one in three college students experience mental health problems during their studies. In the best of cases he or she drops out of higher education without having earned the degree (Chen and Lucock, 2022). Once again, research has shown that college students struggle to find clear meaning or purpose in life (Kosine et al., 2008). Having goals consistent with one's passions and values is correlated with greater mental well-being (Sheldon and Epstein, 2002) and fewer symptoms of depression (Sheldon and Kasser, 1998). For all these reasons, more recent research has focused on a concept that can offer people a way to proactively deal with critical life situations and renew their sense of meaning (Dekker et al., 2020). Life Crafting (henceforth LC) has been defined by Schippers and Ziegler as "a process in which people actively reflect on their present and future life, set goals for important areas of life—social, career, and leisure time—and, if required, make concrete plans and undertake actions to change these areas in a way that is more congruent with their values and wishes" (Schippers and Ziegler, 2019). Finding meaning in our lives is a central tenet of human experience; in fact, individuals tend to actively search for sources of meaning in their lives or consciously enact efforts to create meaning in different areas of life. These overall "Life Crafting" behaviors refer to the conscious efforts individuals exert to create meaning in their lives through cognitively redefining the way they view life, seeking social support systems to manage life's challenges, and actively seeking challenges to facilitate personal growth (Chen et al., 2022). The concept of LC is an entirely new construct in the literature and is based on suggestions from diverse research areas including positive psychology, expressive writing, and the theoretical framework of salutogenesis (Schippers and Ziegler, 2019). An LC intervention can offer people the opportunity to evaluate their goals at a time of uncertainty and rediscover the meaning of life to guide them at a critical time (De Jong et al., 2020). Dekker et al. (2020) argued that LC could improve an individual's goal attainment, performance, and mental health. From these approaches, the basic premise of LC seems to have under consideration the proactive actions that individuals take to discover their values/passions, seek challenges, and accumulate the necessary resources to promote their personal growth and development. In any case, the brief research on the topic seems to agree on some constituent elements of LC intervention (Dekker et al., 2020). Schippers and Ziegler (2019) identify four of them: discovering values and passions, reflecting on one's ideal future, writing specific goals and "if-then" plans, and making public commitments to set goals (Schippers and Ziegler, 2019). De Jong et al.

(2020) also theorized a four-step intervention that echoes those just discussed: values and passions, reflection on one's ideal life, setting specific goals and plans, and public commitment to achieve the set goals (De Jong et al., 2020). According to Chen and Demerouti's model, however, the LC construct possesses a three-factor structure consisting of cognitive crafting, social support seeking and challenge seeking (Chen et al., 2022). Cognitive crafting refers to an individual's ability to proactively reshape the physical, cognitive, and social features of life so that they are perceived as more meaningful. Social support seeking is the behavior of seeking social support systems and networks to achieve personal or professional goals while managing adversity. In this case, meaning is acquired through mutually beneficial relationships. Finally, challenge-seeking is a human need for development and growth, representable as an active effort to increase one's current capabilities through challenging learning opportunities (Chen et al., 2022). The factors just mentioned overlap with three factors from Wrzesniewski and Dutton's (2001) conceptualization of Job Crafting (i.e., cognitive, relational, and task crafting)(Wrzesniewski and Dutton, 2001), and two factors from Tims and Bakker's conceptualization (2016) (i.e., social resource-seeking and challenge augmentation) (Tims and Bakker, 2010). Moreover, LC has been shown to tap into the same conceptual area as Job Crafting; in fact, a positive relationship has been found between LC and proactive personality, between LC and meaning in life, mental health and work engagement; and a negative relationship between LC and job burnout. Recall that Tims et al. (2016) showed that work-crafting behaviors can increase meaningfulness and prevent the onset of work burnout (Tims et al., 2016). Life crafting could be an important predictor of people's mental condition or state. Chen and Demerouti (2022) validated a scale that could provide a measure of the effectiveness of life-crafting interventions (Chen et al., 2022). The questionnaire incorporates the wording of the three dimensions discussed earlier; each dimension consists of three items. The objective of the present study is to validate the Italian version of the Life Crafting Scale.

2 Method: Data analysis

The evaluation of the Life Crafting Scale (LCS) consists of two stages of analysis, where:

- in the first one a Principal Component Analysis (PCA) will be conducted, aimed at investigating the latent structure underlying the Life Crafting Scale and evaluating any sub-scales with reference to the sample used in the study;
- in the second one, the identified sub-scales will be subjected to the Confirmatory Composite Analysis (CCA), a recent method based on PLS-PM which aims to confirm the results obtained in the previous stage.

As suggested by Hair et al. (2019), the two stages are performed by randomly dividing the sample in two sub-samples: a *training sample* equal to 50% of the original sample, where the explorative analysis is executed; a *testing sample* equal to the other 50% of the original sample, where the CCA is conducted for the confirmatory purpose. Subsequently, the methodologies employed and their use will be examined in detail.

2.1 Explorative Analysis (PCA)

Principal Component Analysis (PCA) is a multivariate statistical technique, that analyzes a dataset representing observations described by several dependent variables, which are inter-correlated. Its goal is to explain the variability of a phenomenon preserving as much ‘variability’ as possible, that is, reducing the dimensionality of a dataset with observations on p numerical variables, using a q number of components so that $q < p$ (Jolliffe and Cadima, 2016). PCA was performed on *Jamovi software* and considering Varimax rotation. It was used for exploring the theoretical and latent structure of the scale, to highlight sub-scales in the Life Crafting Scale (LCS) and according to a theoretical background. After this analysis, the Confirmatory Composite Analysis will be performed on the testing sample.

2.2 Confirmatory Composite Analysis for Higher-Order Modelling with PLS (PLS-CCA)

In order to confirm the factor structure, highlighted with the PCA, a Partial Least Squares - Path Model (PLS-PM) with higher order construct was implemented and evaluated using a confirmatory composite analysis (PLS-CCA). PLS-CCA is defined as an emerging and systematic method/process to confirm the measurement model in the partial least squares framework for structural equation modeling (Hair et al., 2019; Henseler et al., 2016; Hair Jr et al., 2019; Schuberth et al., 2018). The analysis was performed using SmartPLS 4 software (Ringle et al., 2022).

2.2.1 The Higher Order Modelling

Observing and basing on the results obtained from the exploratory analysis in the first stage, Life Crafting (LCS) has been conceptualized as a second order latent variable. The latter, also defined as a higher order construct (HOC), has several advantages from both theoretical and empirical considerations (Cheah et al., 2019; Sarstedt et al., 2019; Ciavolino and Nitti, 2013b,a). This type of construct allows the researcher to model a concept and place it on a more abstract level, separating it from its sub-dimensions to be placed on a more concrete dimension (respectively indicated as higher order component - HOC - and lower order components - LOC).

Using modeling helps reduce the number of relationships in the path model so, by using a higher order construct, parsimony can be achieved in a model (Johnson et al., 2011; Polites et al., 2012). Furthermore, especially when (Hair Jr et al., 2018) formative indicators are used, the use of higher order variables can address multicollinearity issues and, in general, the bandwidth-fidelity dilemma (Cronbach and Gleser, 1957) problem.

Higher-order models can be estimated using two methods: Maximum Likelihood Estimation (MLE) and Partial Least Square (PLS). The most widely used is the PLS, also called Hierarchical Component Models (HCM), especially for the various procedures useful for defining the hierarchical structure in the variables - i.e. repeated, two-stage, hybrid indicators - and in the methods for defining the relationships between higher and lower order - i.e. reflective and formative (see Cheah et al. (2019); Sarstedt et al. (2019)).

Although higher order variables in the initial idea of PLS path modeling (Wold, 1982) were not present, subsequent studies have proposed various approaches aimed at estimating higher order latent variables in PLS-SEM. Specifically, there are four approaches: the repeating indicator approach and the extended version (Wold, 1982; Lohmöller, 1989; Becker et al., 2012); the sequential latent variable scoring method or the two-step approach (Becker et al., 2012; Nitti and Ciavolino, 2014; Wetzels et al., 2009; Ringle et al., 2012); the hybrid approach (Bradley and Henseler, 2007) and the recent approach aimed at using the coherent estimation in Mode A (or PLSc) which evaluates the HCM as a compound of common factors (Van Riel et al., 2017). There are several areas of application of the PLS-SEM, such as human resources (Richter et al., 2016; Ringle et al., 2020), psychometrics (Ferrante et al., 2022; Ciavolino et al., 2021), strategic management (Hair et al., 2012a), accounting (Nitzl, 2016).

2.2.2 A reflective-reflective (Type I) measurement model

Researchers need to ensure that measurement theory is adequately developed to be able to use higher-order constructs. Furthermore, the conceptualization and specification of the latter must necessarily be based on this theory of measurement. It is possible to refer to the four types of Higher Order Constructs (HOCs), specified below in table 1 (Becker et al., 2012; Cheah et al., 2019; Ringle et al., 2012).

In the present study the reflective-reflective model was chosen, which implies reflective relationships both between the HOC (LCS) and LOCs (LCS1, LCS2, LCS3), and in the measurement model of the LOCs themselves (therefore between the order constructs bottom and manifest variables - items). Graphically in the reflective-reflective model these types of relationships are characterized by arrows starting from the HOC up to the LOC and then, with arrows from the LOC to the MV - item).

There are two reasons supporting the choice of the reflective-reflective model, explained below: the first reason lies in the high correlation of the LOCs, of which the HOC is the common factor, and the main goal of this study is to derive LOCs distinct reflectors having a HOC as a common factor (Becker et al., 2012; Lohmöller, 1989).

The other motivation that supports the use of the reflective-reflective model is the underlying (soft) psychological theory. In other words, it is the presence of a certain level of Life Crafting in the student that gives rise to LCS1, LCS2, LC3.

2.2.3 Estimation Methods

The estimation of the SEM parameters occurs mainly through two approaches, on the one hand the *parametric approach* with the method of maximum likelihood estimation (MLE) developed by Jöreskog (1970) and on the other hand the *non-parametric approach*, i.e. Wold (1975)'s partial least squares (PLS). Other new *semi-parametric* estimation approaches have been proposed and used in the literature in recent years: the Generalized Structured Component Analysis (Hwang and Takane, 2004) and the

Table 1: Measurement model types

HOCs	Description
Reflective-reflective	It implies a type of reflective relationship between the HOC and the Lower Order Constructs (LOCs) and where the latter are also measured in a reflective way.
Reflective-formative	The HOC represents a more general construct of the reflectively measured LOCs. The specific LOCs do not necessarily share a common cause but rather form the general HOC. This model is employed when a modification in one dimension does not necessarily imply a modification in another, so they do not necessarily co-vary. Rather, each dimension can vary independently of the others (Barroso and Picón, 2012).
Formative-reflective	It includes a more general HOC that explains the formatively measured LOCs. As goal there is the extracting of the common part of formatively measured LOCs, that represent the same theoretical content. However, every LOC builds on a set of different indicators.
Formative-formative	An HCM that determines the relative contribution of the formatively measured LOCs to the more abstract HOC. The purpose of this model is to structure a complex formative construct with many indicators into several sub-constructs, as is the case when researchers subsume several concrete aspects under a more general concept.

Generalized Maximum Entropy (GME) (Ciavolino and Al-Nasser, 2009; Ciavolino and Dahlgaard, 2009; Carpita and Ciavolino, 2017) .

2.2.4 Confirmatory Composite Analysis (PLS-CCA)

Confirmatory composite analysis (PLS-CCA) is a specific type of SEM that aims to evaluate composite models, which consist of a set of constructs that emerge as linear combinations of other variables of interest (Schuberth et al., 2018). In recent years, confirmatory composite analysis has gained traction as a method for confirming measurement quality (MCMQ) in PLS-SEM (Hair Jr et al., 2020). In addition, PLS-CCA is one of the newest methods aimed at confirming and evaluating measurement models in PLS-SEM (Henseler et al., 2014), which corresponds to the non-parametric version of confirmatory factor analysis. With the PLS-CCA the term ”composites” (Rigdon, 2014) takes over in order to clarify the applications and PLS-SEM terminology.

As shown in figure 1, the higher-order measurement model is assessed through a process consisting of two distinct stages:

1. First stage: in the first stage, the evaluation of the lower order measurement model follows the standard steps;
2. Second phase: in the next step, the HOC is evaluated by considering the lower-order constructs as items and not considering the repeated items.

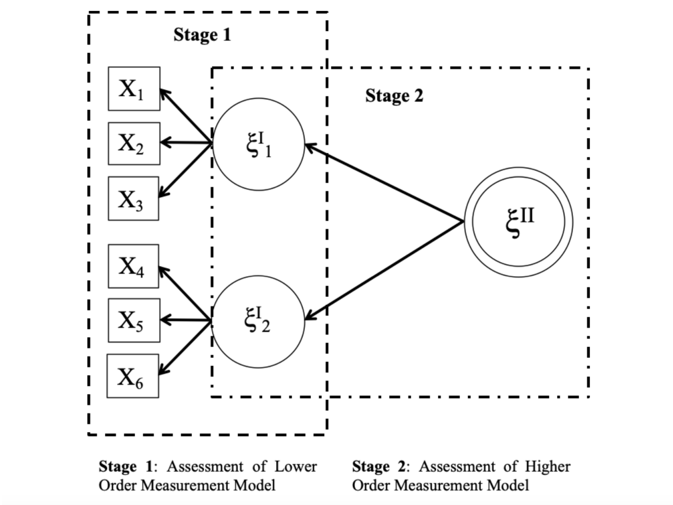

Fig. 1: CCA assessment stages for Higher-Order Model.

This path represents the case study presented in this work (therefore for the reflective-reflective measurement model) and can also be adapted to the remaining types of HOC previously exposed (Becker et al., 2012; Cheah et al., 2019; Ringle et al., 2012). Referring to the two steps defined above, below are the steps to follow to perform a PLS-CCA with reflective-reflective measurement models.

Phase 1: **Stage 1: LOC measurement model assessment**

Step 1: Assessing the indicator loadings and their significance. We need to get a value between $0.40 - 0.708$ for standardized loading (Hulland, 1999) and an associated t-statistic greater than ± 1.96 which is significant for a two-tailed test at level 5% (Hair et al., 2012b) (through the bootstrap procedure);

Step 2: Indicators Reliability (items). It is obtained when the amount of variance, shared between the individual indicator variable and its associated construct, is provided by the quadratic loadings of the individual indicators (Hair et al., 2019);

Step 3: Composite Reliability (construct). In this step, the two reliability criteria Cronbach's alpha (α) and Composite Reliability (*CR*) can be employed. Both indices require a value greater than 0.70. Unweighted Cronbach's alpha is more accurate than composite reliability (which is weighted), because the indicators are not equally reliable;

Step 4: Convergent validity. The value obtained must be equal to/above the 0.50 threshold and is measured by the *Extracted Mean Variance (AVE)*. This index is obtained by calculating the average reliability of the indicator of a construct;

Step 5: Discriminant validity. This step can be evaluated using three criteria: cross-loading, Forner-Lacker criterion (Fornell and Larcker, 1981), and HeteroTrait-MonoTrait (HTMT) (Henseler et al., 2015; Hair et al., 2017). The first method predicts that the outer loadings of items are greater on the respective latent variable, than its cross-loadings on other latent variables. The second Forner-Lacker criterion predicts that the square root of the AVE, of each of the latent variables, should be greater than its correlation with other latent variables. Finally, the HTMT approach can be seen as an estimate of the inter-construct correlation (Nunnally, 1978; Netemeyer et al., 2003), which in case it has a value close to 1 shows a non-discrimination between constructs. HTMT can be used as a criterion, with thresholds of 0.85 (Kline, 2011; Clark and Watson, 2016) and 0.90 (Gold et al., 2001; Teo et al., 2008), or as a bootstrap statistical test ($HTMT_{inference}$), defining the intervals of confidence: if the value one is contained in CI, the two components are not empirically distinct, while if one is outside the intervals, this does not suggest problems of discriminant validity. (Shaffer, 1995; Henseler et al., 2015).

Stage 2: HOC measurement model assessment *Step 1: Reliability*. The *Composite Reliability* is defined as follow:

$$\rho_c = \frac{(\sum_{k=i}^{p} l_i)^2}{(\sum_{k=i}^{p} l_i)^2 + \sum_{k=i}^{p} var(e)_i} \tag{1}$$

where p is the number of LOCs, $(e)_i$ and $var(e)_i$ are respectively the measurement error and its variance of the i^{th} LOC, (note that $(e)_i = 1 - l_i^2$). Since the repeated indicator is estimated by the using a standard PLS-SEM approach, the estimated l_I coincides with the estimated path coefficients between HOC and LOCs. The *Cronbach's Alpha* is defined as follow:

$$\alpha = \frac{p \cdot \bar{r}}{1 + (p-1) \cdot \bar{r}} \tag{2}$$

where $\bar{r}$ is the average of the correlations between the LOCs.

Step 2: Convergent Validity. Assessed by the *AVE* index, is the average of the HOC's squared loadings l_i^2 (squared beta coefficients) between HOC and LOCs:

$$AVE = \frac{\sum_{k=i}^{p} l_i^2}{p} \tag{3}$$

Step 3: Discriminant Validity. This step is based on the same evaluation criteria defined above for the LOCs: cross-loadings, Forner-Lacker and HTMT. In the HOC measurement model the assessment of discriminant validity has to be performed by considering components in a nomological/legal network, meaning the HOC has to be linked to any other exogenous or endogenous variable. In our specific case study, the HOC is specified as a stand-alone component, so it does not make sense to evaluate the discriminant validity.

Step 4: Evaluation of LOC loadings and their significance. In the second stage it is important to remember that also the statistical significance has to be evaluated by bootstrap method.

3 Results

3.1 Sample Description

The dataset used in this study was obtained from a larger web-based survey on University students. The study was performed in the University of Salento situated in the Southern Italy with a total of 953 students aged from 18 to 59 (mean age= 23.2 ± 5.75), among whom 80.9% were female, 19% were male and 0.1% was transgender. The majority of the sample, i.e. (77%), is represented by students attending a bachelor's degree, followed by 20.6% attending a master's degree course and the remaining 2.3% attending a single-cycle master's degree course. Of the entire sample, only 7.3% is out of course and of these 60% are out of course by only one year, 14.3% by two years, 12.9% by three years, 5.7% by fuor years and only 1.4% by five years. The vast majority of the sample states that they have an average of 28 exams taken (13.9%), followed by an average of 29 (12.4%) and an average of 27 (11%). Furthermore, 28.3% of the students carried out an internship and 5.6% claim to have had Erasmus experiences abroad. The origin of the sample is varied, in fact 55% comes from the Department of Human and Social Sciences, 13.9% from the Department of Biological and Environmental Sciences and Technologies, 11.3% from the Department of Economics, 9.5 % from that of Humanities, 6.5% from that of Innovation Engineering, 3.2% from that of Legal Sciences and 0.4% from that of Mathematics and Physics. Finally, the majority of the sample (99%) said they were interested in the "Soft Skill" project.

The written consent and the questionnaire were created and disseminated to the students using the online platform Google Forms, specifying the voluntary nature of the participation and the anonymity of the answers given. Questions were solicited for any doubts and need for clarification.

To confirm the non-normality of the data, the Shapiro-Wilk test was performed. This appears to be appropriate for both small and large sample sizes and has been recommended as a numerical means of assessing data normality (**???**). The test results confirm the non-normality of the data ($p - value < 0.05$).

3.2 Instrument and procedures

The Life Crafting Scale (LCS; Chen et al. (2022)) is a self-report questionnaire composed by 9 items and scores on 5 points Likert (from 1 = "Never" to 5 = "Often").In the present study, the Italian translation of the instrument was developed through a back-translation method (see Appendix).

3.3 PCA results

In order to explore the sub-dimensions of the LCS construct, PCA was performed considering Varimax rotation. The analysis was conducted on the training sample (n=477), considering all the elements of the LCS construct.

If an item group saturated on a component and this set of indicators made sense with respect to psychological theory, this will constitute a subscale of the construct. Below are the results of PCA, with the related items and eigenvalues:

- *First factor* the results confirm the presence of a component on which items CO_CR1, CO_CR2 and CO_CR3 saturate (first eigenvalue = 3.351);
- *Second factor* item SE_SS1, SE_SS2 and SE_SS3 saturate on the same factor (second eigenvalue = 1.772);
- *Third factor* it reveals another a component on which item SE_CH1, SE_CH2 and SE_CH3 saturate (third eigenvalue = 1.204).

Looking at the PCA results, a three-factor solution was revealed and table 2 reports the correlations between the items and the three components: (1) *Component 1*: CO_CR1, CO_CR2 and CO_CR3 ($\xi^{I}{}_{\mathrm{LCS1}}$); (2) *Component 2*: SE_SS1, SE_SS2 and SE_SS3 ($\xi^{I}{}_{\mathrm{LCS2}}$); (3) *Component 3*: SE_CH1, SE_CH2 and SE_CH3 ($\xi^{I}{}_{\mathrm{LCS3}}$).

Table 2: Saturation matrix

	Component		
Items	1	2	3
CO_CR1	0.771		
CO_CR2	0.867		
CO_CR3	0.825		
SE_SS1		0.835	
SE_SS2		0.770	
SE_SS3		0.876	
SE_CH1			0.736
SE_CH2			0.801
SE_CH3			0.808

Note. 'Varimax' rotation was used

In the figure below, the theoretical model's formalization is defined by the path diagram (Figure 2).

The main descriptive statistics on the whole sample for all items (mean, SD mean, SD, Skewness, SE Skewness, Kurtosis and SE Kurtosis) are reported in the table below (Table 3).

$\xi^{I}{}_{\mathrm{LCS1}}$, the first factor, consists of items referring to cognitive crafting; $\xi^{I}{}_{\mathrm{LCS2}}$, the second one, to seeking social support; $\xi^{I}{}_{\mathrm{LCS3}}$, the third one, to seeking challenges.

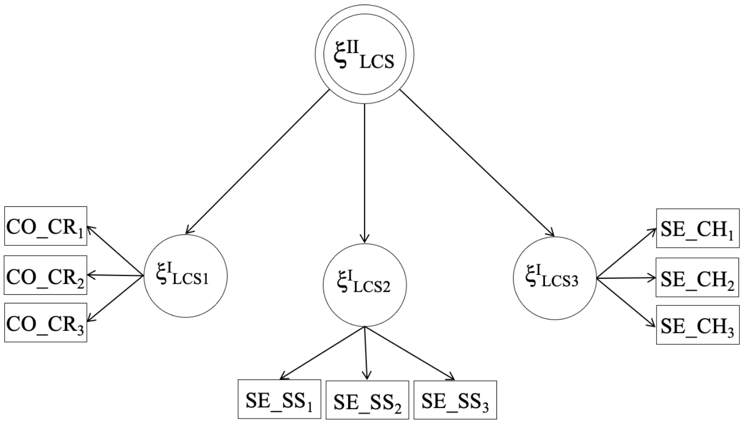

Fig. 2: Theoretical Path Model.

Table 3: Life Crafting Scale Items: Descriptive statistics

Item description	Factor	Mean	SE mean	SD	Skewness	SE skewness	Kurtosis	SE kurtosis
I think about how my life helps others	1	3.68	0.0231	0.713	-0.112	0.0792	-0.0184	0.158
I think about how my actions positively impact my community	1	3.60	0.0235	0.726	-0.107	0.0792	-0.0573	0.158
I think about how my life contributes to society	1	3.51	0.0284	0.878	-0.172	0.0792	-0.182	0.158
I actively seek people's advice when I encounter difficulties	2	3.68	0.0317	0.979	-0.420	0.0792	-0.446	0.158
I seek support from my family when I am down	2	3.54	0.0381	1.18	-0.402	0.0792	-0.767	0.158
I am willing to ask others for help when things get too hard to bear	2	3.62	0.0333	1.03	-0.387	0.0792	-0.506	0.158
I try to work hard on challenging activities	3	4.32	0.0245	0.756	-1.02	0.0792	1.09	0.158
I change my activities to be more challenging	3	3.20	0.0324	1.000	-0.0367	0.0792	-0.338	0.158
I look for opportunities that challenge my skills and abilities	3	3.96	0.0285	0.880	-0.468	0.0792	-0.392	0.158

for Italian translation see the Appendix.

3.4 PLS-CCA results

After the Principal Component Analysis, the Confirmatory Composite Analysis. For the its execution two main stages were followed, i.e. the evaluation of the LOC and HOC measurement model and of the structural model with their steps. The related results for the reflective-reflective measurement model are reported in the following paragraphs.

Stage 1: LOC measurement model assessment

Step 1: Assessing the indicator loadings and their significance. In table 4, all the standardized loadings have a value greater than 0.70 and the associated bootstrap T-statistics reveal them significant.

Step 2: Indicators Reliability (items). All the squared individual indicator loadings (reported in Table 4 above) provides a good measure of the amount of variance shared between each single item and the component on which it saturates;

Step 3: Composite Reliability (construct). This index values are more than acceptable, because the CR (ρ_c) values for each LOCs are respectively equal to 0.864, 0.872, 0.835 and therefore greater than the threshold of 0.700. Also the CR (ρ_a) values for each LOCs are equal to 0.771, 0.783, 0.712 (see Table 5).

Table 4: Indicators loadings and confidence intervals

Relationship	Original Sample	Sample Mean	SD	Confidence Intervals	T Statistics	P Values
${\xi^I}_{\text{LCS1}} \rightarrow$ CO_CR1	0.781	0.780	0.023	[0.730; 0.821]	33.786	0.000
${\xi^I}_{\text{LCS1}} \rightarrow$ CO_CR2	0.882	0.882	0.011	[0.858; 0.903]	77.957	0.000
${\xi^I}_{\text{LCS1}} \rightarrow$ CO_CR3	0.808	0.808	0.023	[0.759; 0.849]	35.168	0.000
${\xi^I}_{\text{LCS2}} \rightarrow$ SE_SS1	0.855	0.855	0.015	[0.824; 0.882]	57.193	0.000
${\xi^I}_{\text{LCS2}} \rightarrow$ SE_SS2	0.780	0.779	0.025	[0.727; 0.824]	31.734	0.000
${\xi^I}_{\text{LCS2}} \rightarrow$ SE_SS3	0.863	0.862	0.014	[0.833; 0.887]	60.898	0.000
${\xi^I}_{\text{LCS3}} \rightarrow$ SE_CH1	0.771	0.770	0.025	[0.717; 0.814]	30.605	0.000
${\xi^I}_{\text{LCS3}} \rightarrow$ SE_CH2	0.741	0.740	0.026	[0.684; 0.787]	28.047	0.000
${\xi^I}_{\text{LCS3}} \rightarrow$ SE_CH3	0.862	0.862	0.012	[0.835; 0.882]	69.264	0.000

Step 4: Convergent validity. The Average Variance Extracted (*AVE*) values, being equal to/exceed the 0.50 threshold for all the LOCs (respectively, $AVE = 0.680, 0.694, 0.629$) are more than acceptable (see Table 5);

Table 5: Reliability and Convergent Validity

	MVs	CR (ρ_c)	CR (ρ_a)	AVE
${\xi^I}_{\text{LCS1}}$	3	0.864	0.771	0.680
${\xi^I}_{\text{LCS2}}$	3	0.8729	0.783	0.694
${\xi^I}_{\text{LCS3}}$	3	0.835	0.712	0.629

Step 5: Discriminant validity. The table 6 shows outer loadings (in bold) between the items and correspondent component greater than the cross-loadings with any other component. The HTMT values (with the bootstrap confidence interval in the parentheses) are all are below the threshold of 0.85, showing a a good distinctiveness (Table 7). Finally, since the square root of AVE of each component is greater than its correlation with other components, also Forner-Lacker criterion is satisfied (see table 8).

Table 6: Crossloading

	${\xi^I}_{\text{LCS1}}$	${\xi^I}_{\text{LCS2}}$	${\xi^I}_{\text{LCS3}}$
CO_CR1	**0.781**	0.243	0.308
CO_CR2	**0.882**	0.284	0.389
CO_CR3	**0.808**	0.304	0.297
SE_SS1	0.326	**0.855**	0.276
SE_SS2	0.252	**0.780**	0.261
SE_SS3	0.259	**0.863**	0.289
SE_CH1	0.323	0.309	**0.771**
SE_CH2	0.266	0.223	**0.741**
SE_CH3	0.365	0.251	**0.862**

It is not necessary to report the discriminant validity between the three composites (${\xi^{II}}_{\text{LCS1}}$, ${\xi^{II}}_{\text{LCS2}}$, ${\xi^{II}}_{\text{LCS3}}$) and the higher order component ${\xi^{II}}_{\text{LCS}}$. The erroneous values of the discriminant validity indices (crossloadings, HTMT and Fornell-Larcker

Table 7: HTMT Matrix and confidence intervals

	${\xi^I}_{\mathrm{LCS1}}$	${\xi^I}_{\mathrm{LCS2}}$
${\xi^I}_{\mathrm{LCS2}}$	0.435 [0.332; 0.533]	
${\xi^I}_{\mathrm{LCS3}}$	0.546 [0.435; 0.653]	0.446 [0.324; 0.562]

Table 8: Fornell-Larcker Criterion

	${\xi^I}_{\mathrm{LCS1}}$	${\xi^I}_{\mathrm{LCS2}}$	${\xi^I}_{\mathrm{LCS3}}$
${\xi^I}_{\mathrm{LCS1}}$	0.825		
${\xi^I}_{\mathrm{LCS2}}$	0.336	0.833	
${\xi^I}_{\mathrm{LCS3}}$	0.404	0.331	0.793

criterion) between these constructs is due to the measurement model of the higher-order component, which repeats the indicators of its four lower-order components.

Stage 2: HOC measurement model assessment

Step 1: Reliability. The *Composite Reliability* being equal to 0.800 and exceeding the threshold of 0.70, provides clear support for the higher-order construct's internal consistency reliability;

$$\rho_c = \frac{(0.780+0.735+0.752)^2}{(0.780+0.735+0.752)^2+(1-0.780^2)+(1-0.735^2)+(1-0.752^2)} \tag{4}$$

Step 2: Convergent Validity. AVE index is equal to 0.571 and indicates good convergent validity, exceeding the threshold of 0.50;

$$AVE = \frac{(0.780^2+0.735^2+0.752^2)}{3} \tag{5}$$

Step 3: Discriminant Validity. Since the HOC is not a nomological network, discriminant validity can not be evaluated for the proposed model;

Step 4: Evaluation of LOC loadings and their significance. Finally, the evaluation of the structural model was carried out using the bootstrap method (with 300 subsamples). The results in the Table 9 reveal the significance of all the relationships of the structural model $(p < 0,05)$. In order, the explained variance of the HOC is mainly due to ${\xi^I}_{\mathrm{LCS1}}$ (0.780) followed by ${\xi^I}_{\mathrm{LCS3}}$ (0.752) and ${\xi^I}_{\mathrm{LCS2}}$ (0.735).

Table 9: Higher-Order Measurement Model (Structural model estimates)

Relationship	Original Sample	Sample Mean	SD	Confidence Intervals	T Statistics	P Values
${\xi^{II}}_{\mathrm{LCS}} \to {\xi^I}_{\mathrm{LCS1}}$	0.780	0.780	0.023	[0.729 ; 0.822]	33.250	0.000
${\xi^{II}}_{\mathrm{LCS}} \to {\xi^I}_{\mathrm{LCS2}}$	0.735	0.735	0.028	[0.673; 0.786]	26.059	0.000
${\xi^{II}}_{\mathrm{LCS}} \to {\xi^I}_{\mathrm{LCS3}}$	0.752	0.752	0.028	[0.693 ; 0.801]	27.169	0.000

The Life Crafting Scale (LCS), in the light of the results obtained in the various phases of evaluation through the CCA, reveals a structure with three composites/factors: LCS can be conceptualized as a higher order construct having three lower order components $\xi^I{}_{\text{LCS1}}$, $\xi^I{}_{\text{LCS2}}$ and $\xi^I{}_{\text{LCS3}}$ (3). Specifically, $\xi^I{}_{\text{LCS1}}$ is composed of items CO_CR1; CO_CR2 and CO_CR3; $\xi^I{}_{\text{LCS2}}$ from items SE_SS1, SE_SS2 and SE_SS3; $\xi^I{}_{\text{LCS3}}$ from SE_CH1, SE_CH2 and SE_CH3 items.

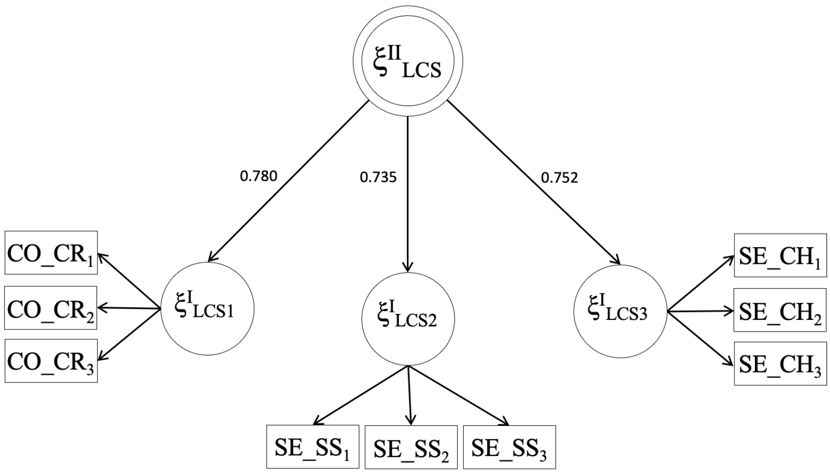

Fig. 3: Path Model with the estimated parameters.

4 Discussion

The results of the present study indicate a three-factor structure of the LCS for Italian college students. Through the use of the CCA, we found support for the appropriateness of a second-order reflective-reflective measurement model of the LCS; more precisely, the LCS is best conceptualized as a second-order reflective-reflexive measurement model. The 3-factor structure is the same as in the original version of the LCS. The three factors of the scale conceptualize life crafting as an active effort to create meaning in one's life through cognitive framing of how life events are interpreted, seeking social support to handle critical life events, and seeking stimulating opportunities to promote personal growth (Chen et al., 2022) . The first factor refers to Cognitive Crafting, understood as an individual's ability to proactively reshape the perception of one's life contexts so as to make them more meaningful. The second factor relates to the search for social support and refers to individuals' need to create social support networks and systems that help them cope with life's adversities. In this sense, meaning is built through the creation of beneficial relationships with others. Finally, the third factor "Seeking challenges" is the set of efforts made by the individual to implement his or her current capabilities and learn new skills suitable for personal growth and mastery of contexts (Chen et al., 2022). The three factors just described take up the conceptualization of Job Crafting, as a set of strategies aimed at creating meaning in one's professional experiences and which implement mental health by reducing the risk of burnout (Wrzesniewski et al., 2013). Compared to the previous study which examined a convenience sample made up of employed persons aged 18 or over, the present study analyzed a sample made up of Italian university students who voluntarily participated by answering the proposed Life Crafting questionnaire. Our first attempt to conceptualize and measure life crafting as a global meaning-making strategy showed encouraging results. Our results support the importance of life crafting as a tool that people can employ to improve their wellness. Life crafting could therefore be important and the alternative strategies that researchers and professionals could use to help their individuals find more meaning in theirs. In other words, we have introduced a new Italian validation scale and anticipate that the life crafting scale will be a useful addition to the arsenal of subjective measures used by contemporary and future researchers to explore the ability to give meaning to one's life and to find/follow a purpose. this is important with a view to targeting actions and services aimed at supporting people in managing and attributing meaning to events in their lives, both at particularly critical moments and in general. This could have different practical implications and a considerable impact on personal and social well-being. Indeed, from the point of view of practical implications, measuring life crafting could be useful for both research and human resources management but also counseling interventions, as identifying and promoting the redefinition of one's life meanings could be a strategy to make individuals aware of the potential of life crafting.

4.1 Limitations and further direction of research

The design is cross-sectional and further studies could consider a longitudinal design. Since life crafting has been considered a self-driven strategy to produce meaning, it is necessary considering the need to have a self-report evaluation changing over time, under different variables (individual and organizational ones). In other words, a longitudinal study could guarantee better quality in the construct evaluation. Furthermore, self-report measures can be a limitation. Self-report measures can determine positive bias, underlying a difference between the own personal opinion (social desirability). In future research, objective indicators such as job performance or physical variables of mental health should be considered. In the end, life crafting can differ in function of demographic and social variables, such as age, gender and geographical context (north or south of Italy represent a crucial difference in terms of the labor market, job opportunities and social services). Future research should consider specific geographical contexts, analyzing objective variables such as career counseling agencies, free services to manage work-life balance, and social programs to support families and special needs (for example, families with children with disabilities). Future studies should consider these variables to develop and propose social local actions to improve the social and working life of people.

5 Disclosure statement

References

Barroso C, Picón A (2012) Multi-dimensional analysis of perceived switching costs. Industrial Marketing Management 41(3):531–543

Becker JM, Klein K, Wetzels M (2012) Hierarchical latent variable models in pls-sem: guidelines for using reflective-formative type models. Long range planning 45(5-6):359–394

Bradley W, Henseler J (2007) Modeling reflective higher-order constructs using three approaches with pls path modeling: a monte carlo comparison

Carpita M, Ciavolino E (2017) A generalized maximum entropy estimator to simple linear measurement error model with a composite indicator. Advances in Data Analysis and Classification 11(1):139–158

Chambers S, Clarke J, Kipping R, Langford R, Brophy R, Hannam K, Taylor H, Willis K, Simpson SA (2022) Parents' perceptions of children's emotional well-being during spring 2020 covid-19 restrictions: A qualitative study with parents of young children in england. Child: Care, Health and Development 48(6):1071–1080

Cheah JH, Ting H, Ramayah T, Memon MA, Cham TH, Ciavolino E (2019) A comparison of five reflective–formative estimation approaches: reconsideration and recommendations for tourism research. Quality & Quantity 53(3):1421–1458

Chen S, van der Meij L, van Zyl LE, Demerouti E (2022) The life crafting scale: development and validation of a multi-dimensional meaning-making measure. Frontiers in psychology 13:166

Chen T, Lucock M (2022) The mental health of university students during the covid-19 pandemic: An online survey in the uk. PloS one 17(1):e0262562

Ciavolino E, Al-Nasser AD (2009) Comparing generalised maximum entropy and partial least squares methods for structural equation models. Journal of nonparametric statistics 21(8):1017–1036

Ciavolino E, Dahlgaard JJ (2009) Simultaneous equation model based on the generalized maximum entropy for studying the effect of management factors on enterprise performance. Journal of applied statistics 36(7):801–815

Ciavolino E, Nitti M (2013a) Simulation study for pls path modelling with high-order construct: A job satisfaction model evidence. In: Advanced dynamic modeling of economic and social systems, Springer, pp 185–207

Ciavolino E, Nitti M (2013b) Using the hybrid two-step estimation approach for the identification of second-order latent variable models. Journal of Applied Statistics 40(3):508–526

Ciavolino E, Ferrante L, Sternativo GA, Cheah JH, Rollo S, Marinaci T, Venuleo C (2021) A confirmatory composite analysis for the italian validation of the interactions anxiousness scale: a higher-order version. Behaviormetrika pp 1–24

Clark LA, Watson D (2016) Constructing validity: Basic issues in objective scale development.

Cronbach LJ, Gleser GC (1957) Psychological tests and personnel decisions.

De Jong EM, Ziegler N, Schippers MC (2020) From shattered goals to meaning in life: life crafting in times of the covid-19 pandemic. Frontiers in psychology

11:577708
Dekker I, De Jong EM, Schippers MC, De Bruijn-Smolders M, Alexiou A, Giesbers B (2020) Optimizing students' mental health and academic performance: Ai-enhanced life crafting. Frontiers in Psychology 11:1063
Fegert JM, Vitiello B, Plener PL, Clemens V (2020) Challenges and burden of the coronavirus 2019 (covid-19) pandemic for child and adolescent mental health: a narrative review to highlight clinical and research needs in the acute phase and the long return to normality. Child and adolescent psychiatry and mental health 14:1–11
Ferrante L, Venuleo C, Sternativo GA, Rollo S, Cheah JH, Salvatore S, Ciavolino E (2022) Relationship between view of context, psychosocial malaise and problematic internet use: mediation analysis using partial least squares structural equation modelling. BJPsych Open 8(4):e121
Fornell C, Larcker DF (1981) Evaluating structural equation models with unobservable variables and measurement error. Journal of marketing research 18(1):39–50
Gold AH, Malhotra A, Segars AH (2001) Knowledge management: An organizational capabilities perspective. Journal of management information systems 18(1):185–214
Hair J, Black W, Babin B, Anderson R (2019) Multivariate data analysis, 8th edn., cengage learning emea, andover. Hampshire
Hair JF, Sarstedt M, Pieper TM, Ringle CM (2012a) The use of partial least squares structural equation modeling in strategic management research: a review of past practices and recommendations for future applications. Long range planning 45(5-6):320–340
Hair JF, Sarstedt M, Ringle CM, Mena JA (2012b) An assessment of the use of partial least squares structural equation modeling in marketing research. Journal of the academy of marketing science 40(3):414–433
Hair JF, Hult GTM, Ringle CM, Sarstedt M, Thiele KO (2017) Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods. Journal of the Academy of Marketing Science 45(5):616–632
Hair Jr JF, Sarstedt M, Ringle CM, Gudergan SP (2018) Advanced issues in partial least squares structural equation modeling. saGe publications
Hair Jr JF, Page M, Brunsveld N (2019) Essentials of business research methods. Routledge
Hair Jr JF, Howard MC, Nitzl C (2020) Assessing measurement model quality in pls-sem using confirmatory composite analysis. Journal of Business Research 109:101–110
Henseler J, Dijkstra TK, Sarstedt M, Ringle CM, Diamantopoulos A, Straub DW, Ketchen Jr DJ, Hair JF, Hult GTM, Calantone RJ (2014) Common beliefs and reality about pls: Comments on rönkkö and evermann (2013). Organizational research methods 17(2):182–209
Henseler J, Ringle CM, Sarstedt M (2015) A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the academy of marketing science 43(1):115–135
Henseler J, Hubona G, Ray PA (2016) Using pls path modeling in new technology research: updated guidelines. Industrial management & data systems

Hulland J (1999) Use of partial least squares (pls) in strategic management research: A review of four recent studies. Strategic management journal 20(2):195–204
Hwang H, Takane Y (2004) Generalized structured component analysis. Psychometrika 69(1):81–99
Johnson RE, Rosen CC, Chang CH (2011) To aggregate or not to aggregate: Steps for developing and validating higher-order multidimensional constructs. Journal of Business and Psychology 26(3):241–248
Jolliffe IT, Cadima J (2016) Principal component analysis: a review and recent developments. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 374(2065):20150202
Jöreskog KG (1970) A general method for estimating a linear structural equation system. ETS Research Bulletin Series 1970(2):i–41
Kline RB (2011) Principles and practice of structural equation modeling (3. baskı). New York, NY: Guilford
Kosine NR, Steger MF, Duncan S (2008) Purpose-centered career development: A strengths-based approach to finding meaning and purpose in careers. Professional School Counseling 12(2):2156759X0801200209
Lohmöller JB (1989) Predictive vs. structural modeling: Pls vs. ml. In: Latent variable path modeling with partial least squares, Springer, pp 199–226
Netemeyer RG, Bearden WO, Sharma S (2003) Scaling procedures: Issues and applications. Sage Publications
Nitti M, Ciavolino E (2014) A deflated indicators approach for estimating second-order reflective models through pls-pm: an empirical illustration. Journal of Applied Statistics 41(10):2222–2239
Nitzl C (2016) The use of partial least squares structural equation modelling (pls-sem) in management accounting research: Directions for future theory development. Journal of Accounting Literature
Nunnally JC (1978) Psychometric Theory 2nd ed. Mcgraw hill book company
Polites GL, Roberts N, Thatcher J (2012) Conceptualizing models using multidimensional constructs: a review and guidelines for their use. European Journal of Information Systems 21(1):22–48
Richter NF, Cepeda-Carrion G, Roldán Salgueiro JL, Ringle CM (2016) European management research using partial least squares structural equation modeling (pls-sem). European Management Journal, 34 (6), 589-597
Rigdon EE (2014) Rethinking partial least squares path modeling: breaking chains and forging ahead. Long Range Planning 47(3):161–167
Ringle CM, Sarstedt M, Straub DW (2012) Editor's comments: a critical look at the use of pls-sem in" mis quarterly". MIS quarterly pp iii–xiv
Ringle CM, Sarstedt M, Mitchell R, Gudergan SP (2020) Partial least squares structural equation modeling in hrm research. The International Journal of Human Resource Management 31(12):1617–1643
Ringle CM, Wende S, Becker JM (2022) Smartpls 4. oststeinbek: Smartpls gmbh
Sarstedt M, Hair Jr JF, Cheah JH, Becker JM, Ringle CM (2019) How to specify, estimate, and validate higher-order constructs in pls-sem. Australasian Marketing Journal (AMJ) 27(3):197–211

Schippers MC, Ziegler N (2019) Life crafting as a way to find purpose and meaning in life. Frontiers in Psychology 10:2778

Schuberth F, Henseler J, Dijkstra TK (2018) Confirmatory composite analysis. Frontiers in psychology 9:2541

Shaffer JP (1995) Multiple hypothesis testing. Annual review of psychology 46(1):561–584

Sheldon KM, Kasser T (1998) Pursuing personal goals: Skills enable progress, but not all progress is beneficial. Personality and social psychology bulletin 24(12):1319–1331

Sheldon SB, Epstein JL (2002) Improving student behavior and school discipline with family and community involvement. Education and urban society 35(1):4–26

Teo TS, Srivastava SC, Jiang L (2008) Trust and electronic government success: An empirical study. Journal of management information systems 25(3):99–132

Tims M, Bakker AB (2010) Job crafting: Towards a new model of individual job redesign. SA Journal of Industrial Psychology 36(2):1–9

Tims M, Derks D, Bakker AB (2016) Job crafting and its relationships with person–job fit and meaningfulness: A three-wave study. Journal of Vocational Behavior 92:44–53

Van Riel AC, Henseler J, Kemény I, Sasovova Z (2017) Estimating hierarchical constructs using consistent partial least squares. Industrial management & data systems

Wetzels M, Odekerken-Schröder G, Van Oppen C (2009) Using pls path modeling for assessing hierarchical construct models: Guidelines and empirical illustration. MIS quarterly pp 177–195

Wold H (1975) Path models with latent variables: The nipals approach. In: Quantitative sociology, Elsevier, pp 307–357

Wold H (1982) Soft modeling: the basic design and some extensions. In: Systems Under Indirect Observation: Causality, Structure, Prediction, Part II, 2., North Holland, Amsterdam, pp 1–54

Wrzesniewski A, Dutton JE (2001) Crafting a job: Revisioning employees as active crafters of their work. Academy of management review 26(2):179–201

Wrzesniewski A, LoBuglio N, Dutton JE, Berg JM (2013) Job crafting and cultivating positive meaning and identity in work. In: Advances in positive organizational psychology, vol 1, Emerald Group Publishing Limited, pp 281–302