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

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**Abstract**
In this study, we highlight Life Crafting Scale (LCS) factor structure and model specifications by using partial least squares structural equations modelling (PLS-SEM) and confirmatory composite analysis (CCA), with a sample of Italian students ($n = 953$). From the validation results obtained through PLS-CCA, we identify the emergence of 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** PLS-CCA · Confirmatory composite analysis · Partial least squares · Structural equation modeling · Life crafting · Multigroup analysis · MICOM

## 1 Introduction

The current global context, deriving from the post-COVID scenario, is characterized by deep uncertainty and instability, from different perspectives: economic, social and even generational. In recent years, alongside the persistent economic crisis, we have experienced an unexpected crisis of public health, an increasingly serious crisis of ideologies, values, and law (Bauman 2015), which has generated or increased a sense of precariousness into a significant proportion of the population. Different manifestations of such a subjective experience have had important repercussions on their self and working frameworks. Over the past decade, research has shown a growing interest in the importance of distal factors in understanding individual and collective health. These factors are considered social determinants of health, i.e. “the conditions in which people are born, grow, work, live and age, and the wider set of forces and systems that shape the

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Extended author information available on the last page of the article conditions of everyday life" (Marmot et al. 2014). In this sense, it is necessary to manage precariousness and indeterminacy by cultivating one's resilience, building satisfying relationships and taking a proactive attitude towards the challenges that life offers us (Boffo et al. 2022).

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 (2019) 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). As evidence of this, an increasing rate of suicide attempts among very young Italian students is currently causing concern (Bersia et al. 2022), even considering those actually carried out: among university students, at least three suicides occurred in 2022, and two more in a single month in 2023. A more in-depth investigation into the factors underlying these choices, in addition to more general mental health issues (Meda et al. 2021), revealed the relevance of the perception of inadequacy in the stages that mark the course of study, together with the parental bond (Tugnoli et al. 2022).

Recent studies carried out in the academic context, have shown that one in three university students experience mental health problems during their studies, with a good resolution of cases where they drop out of higher education without completing their degree (Chen and Lucock 2022). Again, research has shown that university 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). This situation is also reflected in a broader scenario than the university; in fact, focusing on the Italian context, 55% of Italians state that they often think about their mental well-being, an increase of 4 points compared to 2021 (Chambers et al. 2022). Since the outbreak of the COVID-19 pandemic, there have been 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 similar to those of a bereaved person and people feel emptiness and sadness at the loss of their normal life, which can even lead to a loss of meaning in life (Fegert et al. 2020).

It is necessary to reflect and strive to implement one's personal and social resources to self-regulate one's emotions and behavior, build a meaningful life and deal with complexity as responsible social agents throughout life (Marmocchi et al. 2004).

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. 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. 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. 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. A further factor is social support seeking, which is the behavior of looking for 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 fromWrzesniewski and Dutton (2001) conceptualization of Job Crafting (i.e., cognitive, relational, and task crafting), and two factors from Tims and Bakker's conceptualization (i.e., social resource-seeking and challenge augmentation) (Tims et al. 2016).

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. Life crafting could be an important predictor of people's mental condition or state. Chen et al. (2022) validated a scale that could provide a measure of the effectiveness of life-crafting interventions. The questionnaire incorporates the wording of the three dimensions discussed earlier; each dimension consists of three items.

Given these premises, the objective of the present study is to validate the Italian version of the Life Crafting Scale following a component-based approach as an alternative to factor-based ones, such as the model adopted by Chen et al. (2022). In addition to providing a complementary view to factor-based analysis, the composite-based approach enables the use of estimation and validation procedures (e.g. Confirmatory Composite Analysis) that better reflect unequal reliability of indicators and measurement uncertainties (Hair Jr and Sarstedt 2019). The paper is organized as follows: in Sect. 2 the analyses carried out will be detailed, namely the principal component analysis, the confirmatory composite analysis with partial least squares and the multi-group analysis. In Sect. 3, the descriptions of the sample, the tools and procedures used and, finally, the results section relating to the three analyses carried out will be reported. Finally, the discussions with respect to the results obtained are reported in the last paragraphs, comparing them with the theory underlying the research and the conclusions.

## 2 Method: data analysis

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

- in the first a principal components analysis (PCA) will be conducted, to investigate the latent structure of the Life Crafting Scale and evaluate any subscales with reference to the sample used in the study;
- in the second, these subscales identified in the first stage will be subjected to Confirmatory Composite Analysis (PLS-CCA), a method based on PLS-PM which aims to confirm the results obtained in the previous stage;
- in the third, it will be introduced the Multi-Group Analysis and the Measurement Invariance of COmposite Models (MICOM) procedure consisting in a three-step analysis to identify potential between-group differences (i.e. tests of configurational invariance, compositional invariance and composite full invariance as equality of mean and variances).

The first and the second stages specified above are performed on the sample, dividing it into two sub-samples (Hair et al. 2019a). Both samples will be created randomly, obtaining a training sample equal to 50% of the original sample, subjected to exploratory analysis and a test sample equal to the remaining 50% of the original sample, submitted to PLS-CCA for confirmation. 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 aims to analyze a data set with observations represented by several potentially interrelated dependent variables. PCA, through the reduction of initial observations dimensionality, explains the variability of a phenomenon: in other words, the initial $p$ variables will be reduced into $q$ components (obtaining $q < p$) (Jolliffe and Cadima 2016).

*Jamovi software* was used to perform the PCA considering the Varimax rotation. The theoretical and latent structure of the scale are explored, to put in evidence the subscales in the Life Crafting Scale (LCS). After this analysis, the confirmatory composite analysis is performed on the test sample.

### 2.2 Confirmatory composite analysis with PLS for higher-order modelling

The confirmation of the factor structure, highlighted with the PCA, took place using a Partial Least Squares—Path Model (PLS-PM) with a higher-order construct. The evaluation was performed by a confirmatory composite analysis (PLS-CCA). PLS-CCA (or Method of Confirming Measurement Quality'—MCMQ) is a technique for the measurement quality confirmation in partial least squares (PLS) (Hair et al. 2019a; Henseler et al. 2016a; Hair Jr et al. 2019b; Schuberth et al. 2018). This analysis was performed using the SmartPLS 4 software (Ringle et al. 2022).

#### 2.2.1 The higher-order modelling

Looking at the results obtained from the exploratory analysis in the first phase, Life Crafting Scale (LCS) represents a second-order latent variable. The latter, also called Higher-Order Construct (HOC), has numerous advantages both from a theoretical and an empirical point of view (Cheah et al. 2019; Sarstedt et al. 2019a; Ciavolino and Nitti 2013a, b). In particular, 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 place it on a more concrete dimension (indicated as a higher-order component—HOC—and lower-order components—LOC, respectively).

This modeling structure implies that relationships in the path model are minor and the use of a higher-order construct allows getting parsimony in a model (Johnson et al. 2011; Polites et al. 2012). Also, 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 (Cronbach and Gleser 1957) dilemma problem of bandwidth fidelity.

Estimation of higher-order models occurs mainly through three approaches:

1. the parametric approach through the method of maximum likelihood estimation (MLE) (Jöreskog 1970; Bollen et al. 2007);
2. the non-parametric one, with partial least squares (PLS) (Wold 1975).
3. the semi-parametric approaches through the Generalized Structured Component Analysis (Hwang and Takane 2004) and the Generalized Maximum Entropy (GME) (Ciavolino and Al-Nasser 2009; Ciavolino and Dahlgaard 2009; Carpita and Ciavolino 2017).

For the present investigation, the most appropriate approach is the non-parametric one, as it does not rely on distributional requirements; in fact, the sample under examination does not fulfil the normality assumption at a given significance level (see Sect. 3.1), so a non-parametric estimation method represents a proper choice for robust estimation in this situation.

Although higher-order variables were not present in the initial idea of PLS path modelling (Wold 1982), subsequent studies have proposed various approaches aimed at estimating higher-order latent variables in PLS-SEM, in particular Hierarchical Component Models (HCM) (Ciavolino et al. 2022a, b; Ciavolino and Nitti 2013b) with specific types of relationships (reflective or formative) between higher- and lower-order constructs. Different methods can be considered to take into account the hierarchical structure of the variables, such as the repeating indicator approach and its 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 consistent partial least squares (PLSc) in the second-order composites of common factors case (Van Riel et al. 2017). For more details on these methods, see, for example, Cheah et al. (2019); Sarstedt et al. (2019a).

The flexibility of the PLS-SEM approach and the availability of different methodologies for estimation, which are also supported by dedicated software tools, have prompted the application of the PLS-SEM in several areas, such as human resources (Richter et al. 2016; Ringle et al. 2020; Ingusci et al. 2023), psychometrics (Ferrante et al. 2022; Ciavolino et al. 2022a), strategic management (Hair et al. 2012a), and accounting (Nitzl 2016).

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

**Table 1** Measurement model types

| HOCs | Description |
|---|---|
| Reflective–reflective | In this model the relationships between both HOC and LOC and between LOC and items are reflective |
| Reflective-formative | The relationships between HOC and LOC are reflective, while the relationships between LOC and items are formative. In the reflective-formative model, a change in one dimension can be made which does not imply a change in another. In other words, these dimensions do not necessarily co-vary, rather each one varies independently of the remaining (Barroso and Picón 2012) dimensions |
| Formative-reflective | This model contains formative relationships between HOCs and LOCs and reflective relationships between LOCs and items. All LOCs are measured from different groups of items and this model extrapolates the common part of these to reflectively measure HOCs |
| Formative-formative | In this model the relationships both between HOCs and LOCs and between LOCs and items are formative. This type of model makes it possible to obtain a complex educational construct with different sub-dimensions formed by different items, similar to researchers who underlie a more general concept with different concrete aspects |

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.

The reflective–reflective (I type) model was chosen for two reasons, detailed below: the high correlation between the LOCs, which supports the hypothesis of an underlying HOC as a common factor; this allows us to specify a main objective of this study, namely the derivation of distinct reflectors of LOC having a HOC as a common factor (Becker et al. 2012; Lohmöller 1989).

The second motivation supporting the use of this model is the underlying psychological theory: in other words, the origin of the three factors LCS1, LCS2 and LCS3 is derived from students' possession of Life Crafting.

### 2.2.2 Confirmatory composite analysis with partial least squares (PLS-CCA)

PLS-CCA is a specific type of SEM that has the goal of evaluating 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 attraction as a "method for confirming measurement quality" (MCMQ) in PLS-SEM (Hair Jr et al. 2020). In addition, confirmation and evaluation of measurement models in the PLS-SEM can be performed by the new PLS-CCA method (Henseler et al. 2014), which corresponds to the non-parametric version of confirmatory factor analysis (CFA). Within the PLS-CCA, the term "composites" (Rigdon 2014) takes over to clarify the applications and PLS-SEM terminology.

As shown in Fig. 1, the higher-order measurement model is assessed through a series of steps divided into two distinct stages:

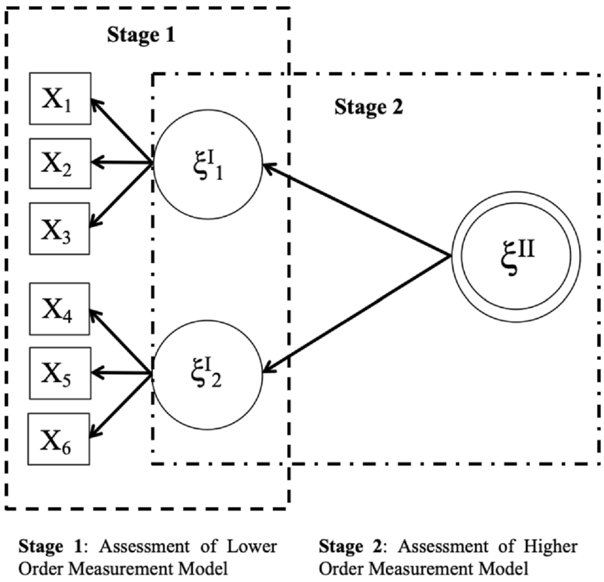


**Fig. 1** The two stages of PLS-CCA assessment for higher-order model

1. First stage: the evaluation of the LOCs follows seven steps, which will be detailed below;
2. Second stage: the HOC is evaluated, where the LOCs constitute the measurement items and the repeated items are not considered. In particular, we point out that the model estimation is carried out considering the repeated indicators approach, while the present phase of the assessment is conducted without relying on repeated items.

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

**Stage 1: Assessment of LOCs measurement model**

Step 1: Indicator loadings and their significance assessment. Through a bootstrap procedure (Hair et al. 2012b), we shall get a value for standardized loading that lies in the interval [0.400; 0.708] (Hulland 1999) with a t-statistic greater than 1.96 in absolute value (significant for a two-tailed test at level 5%);
Step 2: Indicator reliability (items). The variance that is shared by the specific indicator variable and the relative construct constitutes the Indicator Reliability; formally, it is obtained from the quadratic loadings of the individual indicators (Hair et al. 2019a);
Step 3: Composite reliability (construct). In this step, two reliability criteria can be employed, namely Cronbach's Alpha and Composite Reliability. Composite Reliability (CR), which is weighted, is better at measuring internal consistency than Cronbach's Alpha in SEM because CR does not assume the same weight and reliability of each indicator. The last one can be decomposed into ($\rho_c$) and ($\rho_a$) and both indices require a value greater than 0.70 to claim the adequacy of the composite reliability (Purwanto and Sudargini 2021);
Step 4: Convergent validity. Through the extracted mean variance (AVE) it is possible to obtain a value that should be equal to or above the 0.50 threshold. 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 different criteria, that is:

- cross-loading: the items' outer loadings must be greater on the corresponding LV, contrary to the other cross-loadings on the other LVs;
- Fornell–Larcker criterion (Fornell and Larcker 1981): each of the LVs' square root of the AVE must be greater than its correlation with other LVs;
- HeteroTrait–MonoTrait (HTMT) (Henseler et al. 2015; Hair et al. 2017): it represents an estimate of the correlation between the (Nunnally 1978; Netemeyer et al. 2003) constructs, where if the value approaches 1 there is no dis-

crimination between the constructs. There are two ways to use HTML: either as a criterion considering thresholds of 0.85 (Kline 2011; Clark and Watson 2019) or 0.90 (Gold et al. 2001; Teo et al. 2008), or as a bootstrap statistical test ($\text{HTMT}_{\text{inference}}$) by defining the confidence intervals (IC). If 1 is contained in the interval, there is no empirical discrimination between the two variables; on the contrary, the absence of the 1 constitutes a good discrimination between multiple variables (Shaffer 1995; Henseler et al. 2015).

**Stage 2: Assessment of HOCs measurement model**

Step 1: Composite reliability. It is determined as follows:

$$\rho_c = \frac{(\sum_{i=1}^{p} l_i)^2}{(\sum_{i=1}^{p} l_i)^2 + \sum_{i=1}^{p} var(e_i)}, \tag{1}$$

where $p$ is the number of LOCs, $l_i^2$ corresponds to the squared beta coefficient (standardized loading) between HOC and $i$th LOC, $e_i$ represents the measurement error associated with the $i$th LOC, and var($e_i$) is its variance.

The Cronbach Alpha is defined as follows:

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

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

Step 2: Convergent validity. AVE represents the index by which to evaluate the convergent validity and corresponds to the mean of the loadings squared of HOC $l_i^2$ between HOC and LOC:

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

Step 3: Discriminant validity. In this step, as well as in the assessment of LOCs, cross-loadings, Fornell–Larcker and HTMT are the criteria taken into consideration. To be able to evaluate discriminant validity, the HOC must necessarily be linked to another exogenous or endogenous variable. In this specific case study, the absence of connections of the HOC with other variables of the same type does not allow this step to be carried out. In other words, the construct is not part of a nomological/legal network.

Step 4: Evaluation of LOC loadings and their significance. As in the evaluation of LOCs, statistical significance is evaluated with the bootstrap method.

The aforementioned indices are informative on the quality of the model and will be evaluated in the next section. As a final remark, we stress that the suitability of different model fit metrics is still debated in the PLS-CCA framework (Hair Jr et al. 2020, Sec.2). In particular, the CCA analysis evaluates a construct within a nomological network and, hence, its validity and reliability rely on such a structure, also see Becker et al. (2012), Sarstedt et al. (2019b), Shmueli et al. (2019) and Benitez et al. (2020) for more details in this regard. Furthermore, the repeated indicator approach adopted for the model estimation generates highly degenerate empirical covariance and correlation matrices, since their rank (equal to 9) is given by the original indicators, while the repeated ones increase the dimensionality of the matrices ($9 \cdot 2 = 18$) without affecting the rank. This invalidates distance-based indices that rely on the inversion of the empirical covariance matrix; on the other hand, the model-implied correlation matrix uses the redundant information from repeated indicators within a nomological network to generate a full-rank matrix. This provides a structural divergence between the empirical and estimated correlation or covariance matrices that leads us to focus on the aforementioned quality indices.

### 2.2.3 MICOM procedure and multi-group analysis

To evaluate differences among groups a multi-group analysis (PLS-MGA) will be performed. Five based bootstrapping approaches are implemented in SmartPLS software (Hair Jr et al. 2018) and for an extensive discussion, please refer to (Cheah et al. 2020; Chin and Dibbern 2010; Hair Jr et al. 2018; Henseler et al. 2009; Keil et al. 2000; Welch 1947; Sarstedt et al. 2011).

The permutation test approach was chosen in this study, as it has the advantage of controlling type I errors and, moreover, it is relatively conservative compared to the parametric test (Hair Jr et al. 2018; Sarstedt et al. 2011). At last, we will implement the *Measurement Invariance of COmposite Models* (MICOM) procedure (Henseler et al. 2016b; Matthews 2017; Cheah et al. 2020). This method consists of a three-step analysis to identify potential between-group differences, namely, tests of configurational invariance, compositional invariance, and composite full invariance as equality of mean and variances. The three steps are carried out sequentially:

- The first step qualitatively assesses the occurrence of the same nomological framework and indicators between the two groups, as well as the adoption of the same data analysis procedures (data pre-processing and algorithms). This step is automatically checked in the present study.
- Then, the procedure focuses on composite scores and checks if there are differences between their formation in two groups: formally, the correlation between the composite scores obtained from the weight vectors resulting from the two groups is compared to the quantile of the empirical distribution of such correlations obtained from permuting the elements between groups. If the correlation is less than the $\alpha$-level quantile (here, $\alpha = 0.05$, then we reject the configurational invariance hypothesis.
- The third step of the MICOM procedure focuses on mean and variance of the composite between the groups. Also in this case, permutations are used to obtain an empirical distribution of mean (respectively, log-variance) differences derived from the two composites. If the original group difference between means (respectively, log-variances) lies outside the two-sided $(1 - \alpha)$-confidence interval constructed from this empirical distribution (choosing again $\alpha = 0.05$), we reject the mean (respectively, variance) hypothesis.

If MICOM provides evidence of potential heterogeneity or group differences, it is appropriate to carry out the whole multi-group analysis. This procedure complements the estimates obtained from the overall model (i.e., without grouping) with the inclusion of the evaluation of the same model estimated on individual groups. The statistical significance of the between-group estimates in the multi-group analysis can be carried out using a permutation-based approach, in line with the implementation of the phases of the MICOM procedure discussed above. More details on this procedure can be found in Henseler et al. (2016b).

## 3 Results

### 3.1 Sample description

For the study, a sample of University students and recent graduates enrolled at the University in Southern Italy was recruited through a non-probabilistic sampling for convenience, in which the subjects are selected for their easy accessibility and proximity to the researcher. Data collection began after the approval of the research project by this Ethics Committee on 13/05/2022 with the members of the Commission, appointed on 27/04/2020 with resolution no. 54 by the Council of the Department of the University. Furthermore, data were collected by means of telematic diffusion of the questionnaire through official communication to the working group and through the main means of communication on the web and social media. The sample is composed by 953 subjects aged from 18 to 59 (mean = 23.2, median = 21), among whom 80.9% were female, 19% were male, and 0.1% were 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 all the units composing the sample, only 7.3% are beyond the allotted time to attain a degree and, among them, 60% are beyond the allotted time by only 1 year, 14.3% by 2 years, 12.9% by 3 years, 5.7% by 4 years, and only 1.4% by 5 years. The vast majority of the respondents in the sample state 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 and Life Skills" project.

Both the written consent and the questionnaire were created and disseminated to the students using the online platform Google Forms. The voluntary participation in the research and the guarantee of anonymity were highlighted in the consent. Questions were solicited for any doubts and need for clarification. No missing values were reported for the items included in the measurement model since they were set as mandatory.

The univariate normality test was conducted for all the nine variables using, for each Shapiro–Wilk test, the whole sample. This appears to be appropriate for both small and large sample sizes and has been recommended as a numerical means of assessing data normality (Ghasemi and Zahediasl 2012; Motulsky 2014; Das and Imon 2016). 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 containing 9 items, each characterized by scores on 5 Likert points (from 1 = "Never" to 5 = "Often"). Both English and Italian versions are listed in the appendix (see, respectively, Appendix A and B).

### 3.3 PCA results

To explore the sub-dimensions of the LCS construct, PCA was performed considering Varimax rotation. The analysis was conducted on the training sample ($n = 477$).

If an item group saturates on the same component and the psychological theory supports merging these indicators, this constitutes a subscale of the construct. Below are PCA's results, with the related items and eigenvalues:

- *First factor* confirms the presence of a component where 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 in Table 2 are shown the correlations between the items and the three components: (1) Component 1: CO_CR1, CO_CR2 and CO_CR3 ($\xi^{\mathrm{I}}{}_{\mathrm{LCS1}}$); (2) Component 2: SE_SS1, SE_SS2 and SE_SS3 ($\xi^{\mathrm{I}}{}_{\mathrm{LCS2}}$); (3) Component 3: SE_CH1, SE_CH2 and SE_CH3 ($\xi^{\mathrm{I}}{}_{\mathrm{LCS3}}$).

In the path diagram below (Fig. 2) the formalization of the theoretical model is revealed.

Following the results of main descriptive statistics on the whole sample and for all items (mean, SD mean, SD, Skewness, SE Skewness, Kurtosis, and SE Kurtosis) (Table 3).

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

**Table 2** Saturation matrix

| Items | Component 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 |

‘Varimax’ rotation was used

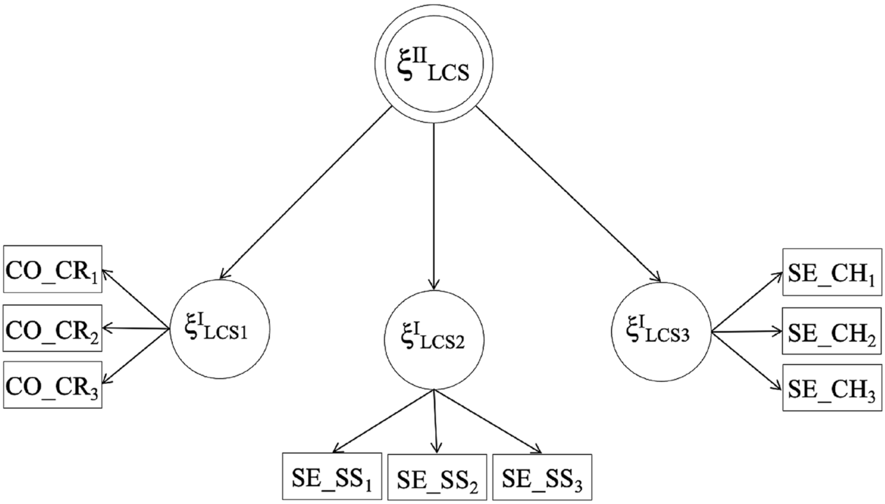


**Fig. 2** Theoretical path model

## 3.4 PLS-CCA results

After the Principal Component Analysis, the Confirmatory Composite Analysis was carried out on the test sample. For 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: Assessment of LOC measurement 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

**Table 4** Indicators loadings and confidence intervals

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

**Table 5** Reliability and convergent validity

| | MVs | CR ($\rho_c$) | CR ($\rho_a$) | AVE |
|---|---|---|---|---|
| $\xi^{I}_{LCS1}$ | 3 | 0.864 | 0.771 | 0.680 |
| $\xi^{I}_{LCS2}$ | 3 | 0.8729 | 0.783 | 0.694 |
| $\xi^{I}_{LCS3}$ | 3 | 0.835 | 0.712 | 0.629 |

Step 1: Indicator loadings and their significance assessment. All the standardized loadings values are greater than the threshold 0.70, with a correspondent bootstrap *t*-statistics revealing them as significant (Table 4).

Step 2: Indicators Reliability (items). The variance shared between each item and the corresponding component is significant. This variance is given by each squared loading of the single indicators (Table 4);

Step 3: Composite Reliability (construct). Being both the CR values ($\rho_c$) respectively at each LOC equal to 0.864, 0.872, 0.835 and the CR values ($\rho_a$) of each LOC equal to 0.771, 0.783, 0.712, all exceed the 0.700 threshold and represent good composite reliability (see Table 5).

Step 4: Convergent validity. Since all the values of average variance extracted (AVE) are greater than or equal to the threshold of 0.50 (specifically 0.680, 0.694, 0.629), a good convergent validity is guaranteed (Table 5).

Step 5: Discriminant validity. As anticipated, there are three criteria for performing and evaluating this step. In this case, all three satisfy discriminant validity: the outer loadings reported in bold (between the items and the corresponding component) are greater than those with the remaining components (Table 6); the HTMT threshold of 0.85 is not exceeded in any case and this guarantees high distinctiveness (Table 7 with the related bootstrap confidence intervals); the Fornell–Larcker criterion is satisfied, as the square root of the AVE of each component is greater than its correlation with the other components (see Table 8).

Report the discriminant validity between the three sub-components ($\xi^{I}_{LCS1}$, $\xi^{I}_{LCS2}$, $\xi^{I}_{LCS3}$) and that of higher order $\xi^{II}_{LCS}$ is not needed in this case. The erroneous values of the discriminant validity indices (cross-loadings, HTMT, and

**Table 6** Crossloading

| | $\xi^{I}_{LCS1}$ | $\xi^{I}_{LCS2}$ | $\xi^{I}_{LCS3}$ |
|---|---|---|---|
| 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** |

**Table 7** HTMT Matrix and confidence intervals

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

**Table 8** Fornell–Larcker criterion

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

Fornell–Larcker criterion) among these constructs are caused by the repetition of items related to the three lower-order components in the measurement model of the higher-order component.

**Stage 2: Assessment of the HOC measurement model**

Step 1: Composite Reliability. The higher-order construct's internal consistency reliability is guaranteed by the relative value (0.800) greater than the threshold equal to 0.700.

$$\rho_c = \frac{(0.780 + 0.735 + 0.752)^2}{(0.780 + 0.735 + 0.752)^2 + (1 - 0.780^2) + (1 - 0.735^2) + (1 - 0.752^2)} \\ =0.7999. \tag{4}$$

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

**Table 9** Higher-order measurement model (structural model estimates)

| Relationship | Original sample | Sample mean | SD | Confidence intervals | *T* statistics | *p* values |
|---|---|---|---|---|---|---|
| $\xi^{II}{}_{LCS} \rightarrow \xi^{I}{}_{LCS1}$ | 0.780 | 0.780 | 0.023 | [0.729; 0.822] | 33.250 | 0.000 |
| $\xi^{II}{}_{LCS} \rightarrow \xi^{I}{}_{LCS2}$ | 0.735 | 0.735 | 0.028 | [0.673; 0.786] | 26.059 | 0.000 |
| $\xi^{II}{}_{LCS} \rightarrow \xi^{I}{}_{LCS3}$ | 0.752 | 0.752 | 0.028 | [0.693; 0.801] | 27.169 | 0.000 |

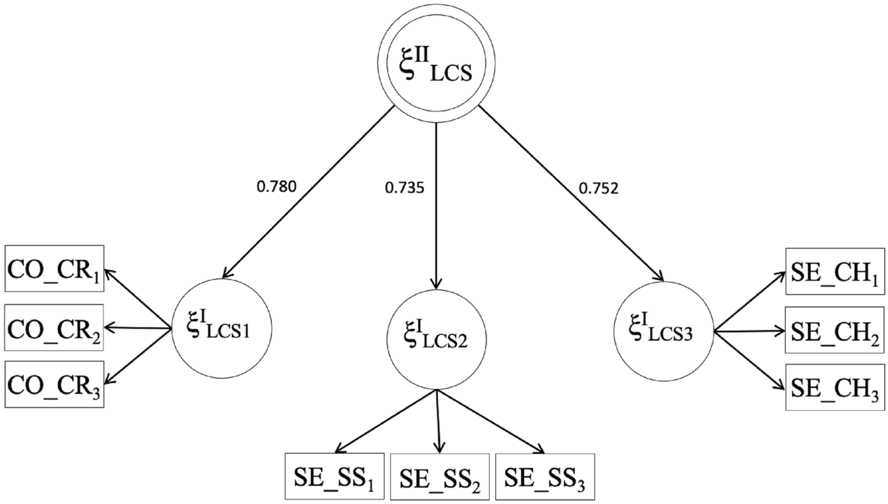


**Fig. 3** Path model and relatives estimated parameters

$$AVE = \frac{(0.780^2 + 0.735^2 + 0.752^2)}{3} = 0.571. \quad (5)$$

Step 3: Discriminant validity. Discriminant validity cannot be evaluated for the proposed model, as the higher-order construct is not inserted in a nomological network.

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 sub-samples). The results in Table 9 reveal the significance of all the relationships of the structural model ($p$ value < 0.05). The explained HOC variance derives primarily from $\xi^{I}{}_{LCS1}$ (0.780), and then from the rest $\xi^{I}{}_{LCS3}$ (0.752) and $\xi^{I}{}_{LCS2}$ (0.735).

In the light of the results obtained in the various phases of evaluation through the PLS-CCA, the Life Crafting Scale (LCS) contains within it three composites ($\xi^{I}{}_{LCS1}$, $\xi^{I}{}_{LCS2}$ and $\xi^{I}{}_{LCS3}$) and a higher-order construct, i.e. LCS (3). Specifically, $\xi^{I}{}_{LCS1}$ is composed of items CO_CR1; CO_CR2 and CO_CR3; $\xi^{I}{}_{LCS2}$ from items SE_SS1, SE_SS2 and SE_SS3; $\xi^{I}{}_{LCS3}$ from SE_CH1, SE_CH2 and SE_CH3 items (Fig. 3).

### 3.5 MICOM procedure and multi-group analysis results

As a final step in our analysis, we check whether significant differences between groups arise in the measurement or the structural models. Here, we consider three primary variables to delve into the invariance of the model between different groups, namely, age, degree program, and sex of the respondents.

To carry out this analysis, we perform pairwise comparisons between groups identified by such variables while guaranteeing that each involved in this study contains (at least) 124 units: this value for the classwise sample size relies on Cohen's criteria for statistical power and its specification in PLS-SEM modeling, see e.g. Matthews (2017, Table 10.1) and references therein. In particular, the value is chosen in relation to the specific significance level ($\alpha = 0.05$), statistical power (0.8), and minimum $R^2$ value (0.25).

Referring to the aforementioned classifying variables master data, two "sex" classes and two "age" classes are considered. We focus only on two sex classes as a single transgender respondent does not allow a proper group comparison. As per the choice of the age classes, they are defined by the intervals [18, 22[ and [22, 59], being 18 and 59 the minimal and the maximal ages of the respondents, respectively. The definition of the cut-off for the two "*age*" classes is motivated by three reasons: the median of the sample is 21, as already mentioned above; the numerosities of the two classes are comparable; it is worth exploring the potential match between the grouping based on the "age" and the "degree type" variables. Regarding the latter, it involves two classes, namely a 3-year/Bachelor's degree program and a 2-year/Master's degree program. While the classification derived from the "age" variable is properly balanced (489 units in the [18; 22[ class and 465 units in the [22; 59] class), the "sex" and "degree type" variables generate unbalanced classes. For this reason, we also considered additional tests by carrying out the multi-group analysis with balanced subsamples for these two grouping variables, with the aim of assessing the adherence of the outcomes with the results of analysis on the whole sample, which we report below.

The following Tables 10, 11, and 12 report the main results of the MICOM analysis for the "age", "degree type", and "sex" groupings, respectively.

Based on the definitions provided in Sect. 2.2.3, all the first-order constructs show partial (i.e., up to compositional) invariance under the grouping based on "age". The only construct that does not enjoy full compositional invariance is $\xi^{\mathrm{I}}_{\mathrm{LCS3}}$ due to a group effect on the mean. Note that the way information is composed to estimate the higher-order construct makes it non-invariant even at the compositional level.

The grouping based on "degree type" returns a deviation from partial invariance, as $\xi^{\mathrm{I}}_{\mathrm{LCS3}}$ does not enjoy compositional invariance. Mean invariance should also be rejected for $\xi^{\mathrm{I}}_{\mathrm{LCS2}}$, while the results for $\xi^{\mathrm{I}}_{\mathrm{LCS1}}$ suggest full invariance.

The last grouping based on "sex" also shows a lack of partial invariance for the first-order construct $\xi^{\mathrm{I}}_{\mathrm{LCS2}}$. While $\xi^{\mathrm{I}}_{\mathrm{LCS3}}$ is variance-, but not mean-invariant, also in this case $\xi^{\mathrm{I}}_{\mathrm{LCS1}}$ is fully invariant.

MICOM provides us with evidence that leads us to proceed with the multi-group analysis. In Tables 13, 14, and 15 we provide the estimates of the effects

**Table 10** Summary of results from MICOM: age classes are defined by the intervals [18; 22[ and [22; 59[

| | $\xi^{\mathrm{I}}_{\mathrm{LCS1}}$ | $\xi^{\mathrm{I}}_{\mathrm{LCS2}}$ | $\xi^{\mathrm{I}}_{\mathrm{LCS3}}$ | $\xi^{\mathrm{II}}_{\mathrm{LCS}}$ |
|---|---|---|---|---|
| Corr. | 0.9998 | 0.9997 | 0.9999 | 0.9975 |
| 5.0% quantile | 0.9992 | 0.9989 | 0.9985 | 0.9980 |
| *p* value (corr.) | 0.3909 | 0.3951 | 0.7266 | 0.0205 |
| Comp. invariance | Yes | Yes | Yes | No |
| Mean diff. | −0.0395 | −0.0985 | −0.1673 | −0.1341 |
| 5% CI (mean) | [−0.1299;0.1264] | [−0.1258;0.1292] | [−0.1251;0.1277] | [−0.1300;0.1286] |
| *p* value (mean) | 0.5401 | 0.1289 | 0.0115 | 0.0415 |
| Mean invariance | Yes | Yes | No | No |
| Var. diff. | −0.0324 | 0.0249 | 0.0033 | −0.0250 |
| 5% CI (var.) | [−0.1772;0.1749] | [−0.1561;0.1610] | [−0.1840;0.1839] | [−0.1862;0.1866] |
| *p* value (var.) | 0.7210 | 0.7652 | 0.9722 | 0.7874 |
| Var. invariance | Yes | Yes | Yes | Yes |

**Table 11** Summary of results from MICOM: degree classes are defined by 3-year/Bachelor degree program and 2-year/Master degree program

| | $\xi^{\mathrm{I}}_{\mathrm{LCS1}}$ | $\xi^{\mathrm{I}}_{\mathrm{LCS2}}$ | $\xi^{\mathrm{I}}_{\mathrm{LCS3}}$ | $\xi^{\mathrm{II}}_{\mathrm{LCS}}$ |
|---|---|---|---|---|
| Corr. | 0.9995 | 0.9999 | 0.9969 | 0.9989 |
| 5.0% quantile | 0.9990 | 0.9986 | 0.9981 | 0.9976 |
| *p* value (corr.) | 0.2239 | 0.7053 | 0.0106 | 0.2811 |
| Comp. invariance | Yes | Yes | No | Yes |
| Mean diff. | −0.0656 | −0.2102 | −0.1899 | −0.2039 |
| 5% CI (mean) | [−0.1384;0.1376] | [−0.1394;0.1406] | [−0.1377;0.1408] | [−0.1384;0.1403] |
| *p* value (mean) | 0.3424 | 0.0030 | 0.0065 | 0.0042 |
| Mean invariance | Yes | No | No | No |
| Var. diff. | −0.0291 | 0.0302 | −0.0599 | −0.0205 |
| 5% CI (var.) | [−0.1814;0.2018] | [−0.1666;0.1765] | [−0.1948;0.2041] | [−0.1921;0.2064] |
| *p* value (var.) | 0.7662 | 0.7262 | 0.5690 | 0.8393 |
| Var. invariance | Yes | Yes | Yes | Yes |

and quality metrics of model estimation, both on the whole sample and considering individual groups.

The outcomes of the multi-group analysis give a complementary view with respect to the results of MICOM. We look at Table 13 to evaluate the extent of group differences in relation to the overall model studied in the previous sections. Specifically, we take the maximum and minimum path coefficient estimates, normalizing these differences to the estimate of the overall model. Hence we evaluate the ratios

**Table 12** Summary of results from MICOM based on sex (female/male)

| | $\xi^{I}_{LCS1}$ | $\xi^{I}_{LCS2}$ | $\xi^{I}_{LCS3}$ | $\xi^{II}_{LCS}$ |
|---|---|---|---|---|
| Corr. | 10,000 | 0.9963 | 0.9988 | 0.9989 |
| 5.0% quantile | 0.9985 | 0.9980 | 0.9973 | 0.9965 |
| *p* value (corr.) | 0.9928 | 0.0088 | 0.2116 | 0.4268 |
| Comp. invariance | Yes | No | Yes | Yes |
| Mean diff. | 0.1572 | 0.2932 | 0.2045 | 0.2895 |
| 5% CI (mean) | [−0.1603;0.1612] | [−0.1575;0.1620] | [−0.1614;0.1658] | [−0.1553;0.1609] |
| *p* value (mean) | 0.0550 | 0.0005 | 0.0121 | 0.0002 |
| Mean invariance | Yes | No | No | No |
| Var. diff. | −0.0914 | −0.0567 | −0.0496 | −0.0292 |
| 5% CI (var.) | [−0.2118;0.2343] | [−0.1901;0.2107] | [−0.2240;0.2496] | [−0.2158;0.2461] |
| *p* value (var.) | 0.4240 | 0.5843 | 0.6774 | 0.8084 |
| Var. invariance | Yes | Yes | Yes | Yes |

**Table 13** Global and groupwise path coefficients

| | Overall | 18-21 | 22+ | F | M | Deg1 | Deg2 |
|---|---|---|---|---|---|---|---|
| $\xi^{II}_{LCS} \rightarrow \xi^{I}_{LCS1}$ | 0.7806 | 0.8044 | 0.7646 | 0.7782 | 0.7903 | 0.7911 | 0.7653 |
| $\xi^{II}_{LCS} \rightarrow \xi^{I}_{LCS2}$ | 0.6912 | 0.6212 | 0.7491 | 0.6945 | 0.6742 | 0.6723 | 0.7286 |
| $\xi^{II}_{LCS} \rightarrow \xi^{I}_{LCS3}$ | 0.7599 | 0.7873 | 0.7333 | 0.7630 | 0.7382 | 0.7690 | 0.7369 |

**Table 14** Global and groupwise outer loadings

| | Overall | 18–21 | 22+ | F | M | Deg1 | Deg2 |
|---|---|---|---|---|---|---|---|
| $\xi^{I}_{LCS1} \rightarrow$ CO_CR1 | 0.7918 | 0.7702 | 0.8166 | 0.7812 | 0.8262 | 0.7754 | 0.8348 |
| $\xi^{I}_{LCS1} \rightarrow$ CO_CR2 | 0.8832 | 0.8695 | 0.8997 | 0.8786 | 0.9049 | 0.8750 | 0.9077 |
| $\xi^{I}_{LCS1} \rightarrow$ CO_CR3 | 0.8273 | 0.8071 | 0.8476 | 0.8200 | 0.8533 | 0.8128 | 0.8646 |
| $\xi^{I}_{LCS2} \rightarrow$ SE_SS1 | 0.8471 | 0.8492 | 0.8453 | 0.8610 | 0.8010 | 0.8408 | 0.8602 |
| $\xi^{I}_{LCS2} \rightarrow$ SE_SS2 | 0.8010 | 0.8016 | 0.7980 | 0.7900 | 0.8363 | 0.7991 | 0.8015 |
| $\xi^{I}_{LCS2} \rightarrow$ SE_SS3 | 0.8609 | 0.8635 | 0.8594 | 0.8638 | 0.8457 | 0.8607 | 0.8600 |
| $\xi^{I}_{LCS3} \rightarrow$ SE_CH1 | 0.7669 | 0.7510 | 0.7787 | 0.7770 | 0.7169 | 0.7715 | 0.7509 |
| $\xi^{I}_{LCS3} \rightarrow$ SE_CH2 | 0.7690 | 0.7474 | 0.7896 | 0.7654 | 0.7757 | 0.7325 | 0.8399 |
| $\xi^{I}_{LCS3} \rightarrow$ SE_CH3 | 0.8644 | 0.8727 | 0.8572 | 0.8695 | 0.8467 | 0.8596 | 0.8841 |

All the reported values are significant

**Table 15** Global and groupwise quality criteria

| | | Overall | 18-21 | 22+ | F | M | Deg1 | Deg2 |
|---|---|---|---|---|---|---|---|---|
| $\xi_{\mathrm{LCS1}}v$ | $R^2$ | 0.6094 | 0.6471 | 0.5847 | 0.6056 | 0.6246 | 0.6258 | 0.5856 |
| | AVE | 0.6971 | 0.6669 | 0.7316 | 0.6849 | 0.7432 | 0.6759 | 0.7561 |
| | $\rho_c$ | 0.8733 | 0.8570 | 0.8909 | 0.8667 | 0.8966 | 0.8619 | 0.9028 |
| | $\rho_a$ | 0.7864 | 0.7574 | 0.8175 | 0.7741 | 0.8310 | 0.7665 | 0.8382 |
| $\xi^{\mathrm{I}}_{\mathrm{LCS2}}$ | $R^2$ | 0.4777 | 0.3859 | 0.5611 | 0.4823 | 0.4545 | 0.4520 | 0.5309 |
| | AVE | 0.7001 | 0.7031 | 0.6966 | 0.7038 | 0.6854 | 0.6954 | 0.7073 |
| | $\rho_c$ | 0.8749 | 0.8765 | 0.8731 | 0.8768 | 0.8672 | 0.8725 | 0.8786 |
| | $\rho_a$ | 0.7856 | 0.7905 | 0.7816 | 0.7939 | 0.7842 | 0.7807 | 0.7946 |
| $\xi^{\mathrm{I}}_{\mathrm{LCS3}}$ | $R^2$ | 0.5774 | 0.6198 | 0.5377 | 0.5822 | 0.5449 | 0.5914 | 0.5430 |
| | AVE | 0.6422 | 0.6280 | 0.6549 | 0.6485 | 0.6108 | 0.6235 | 0.6836 |
| | $\rho_c$ | 0.8429 | 0.8344 | 0.8504 | 0.8466 | 0.8242 | 0.8318 | 0.8658 |
| | $\rho_a$ | 0.7275 | 0.7128 | 0.7407 | 0.7356 | 0.6938 | 0.7058 | 0.7870 |
| $\xi^{\mathrm{II}}_{\mathrm{LCS}}$ | $\rho_c$ | 0.8439 | 0.8354 | 0.8514 | 0.8441 | 0.8377 | 0.8389 | 0.8541 |
| | $\rho_a$ | 0.7950 | 0.7876 | 0.8051 | 0.7956 | 0.7905 | 0.7889 | 0.8112 |

All the reported values are significant, except for $\rho_a$ for $\xi^{\mathrm{I}}_{\mathrm{LCS3}}$ in the sex "M" group

$$\mu^{\mathrm{age}}_{\mathrm{LCS1}} := \frac{\max\left\{\beta^{18\text{-}21}_{\xi^{\mathrm{II}}_{\mathrm{LCS}}\to\xi^{\mathrm{I}}_{\mathrm{LCS1}}}, \beta^{22+}_{\xi^{\mathrm{II}}_{\mathrm{LCS}}\to\xi^{\mathrm{I}}_{\mathrm{LCS1}}}\right\} - \min\left\{\beta^{18\text{-}21}_{\xi^{\mathrm{II}}_{\mathrm{LCS}}\to\xi^{\mathrm{I}}_{\mathrm{LCS1}}}, \beta^{22+}_{\xi^{\mathrm{II}}_{\mathrm{LCS}}\to\xi^{\mathrm{I}}_{\mathrm{LCS1}}}\right\}}{\beta^{\mathrm{overall}}_{\xi^{\mathrm{II}}_{\mathrm{LCS}}\to\xi^{\mathrm{I}}_{\mathrm{LCS1}}}} \tag{6}$$

and analogous indices for other construct and grouping variables. The highest effect is observed for $\xi^{\mathrm{II}}_{\mathrm{LCS}} \to \xi^{\mathrm{I}}_{\mathrm{LCS2}}$ with a relevant group difference for estimates based on the "age" classification (18.50%). Remarkably, the same first-order construct $\xi^{\mathrm{I}}_{\mathrm{LCS2}}$ and grouping variable "age" also produce the highest between-group differences for the $R^2$ coefficient (36.68%), which is obtained adapting (6) in relation to the original $R^2$ value.

Summarizing the results, it is manifest that the most relevant group differences arise:

– in the construct $\xi^{\mathrm{I}}_{\mathrm{LCS2}}$ related to " Social Support" for the classifications based on "sex".
– in the construct $\xi^{\mathrm{I}}_{\mathrm{LCS3}}$ related to "Seeking Challenges" in the classification by "degree type" and "age", which corroborates the similarities between the "age" and "degree type" classifications. However, the influence of the latter variable only arises in the third stage of MICOM procedure and, in particular, in the test for mean invariance, so we can speak of partial invariance.

For the sake of completeness, we note that the higher-order construct $\xi^{\mathrm{II}}_{\mathrm{LCS}}$ also shows group effects, in particular in the "age" grouping. These results are in line with the additional tests carried out on balanced subsamples for the "degree type" and "sex" groupings.

## 4 Discussion

The results of the present study indicate a three-factor solution for the Italian LCS validation. Through the PLS-CCA, we chose a second-order reflective–reflective measurement model for the LCS; The LCS can be defined as a second-order reflective–reflective measurement model. The 3-factor structure is the same as 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, in line with previous studies (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 define a conceptual basis for a set of strategies that 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.

The results of the study showed significant differences in the dimensions "social support seeking" and "challenge seeking" with respect to the different groups (gender, age and type of degree).

In particular, the sample reported higher social support seeking scores in women. These results are congruent with previous research (Kugbey et al. 2015; Tahmasbipour and Taheri 2012), which showed that female students report higher levels of social support than their male counterparts (Kugbey et al. 2015; Tahmasbipour and Taheri 2012). The higher level among females could be explained on the basis of their help-seeking behaviour as reported in the literature (Alsubaie et al. 2019). It is likely that women are more vulnerable to stressors (Misra and McKean 2000), but are more adept at using social sources to manage stressors than men (Camara et al. 2017; Rose and Rudolph 2006).

Further results indicated significative differences between the age groups (18-22/22+) in the challenge-seeking construct. Participants over 22 years enrolled in a second-level degree reported higher levels of challenges seeking. As already discussed, challenge-seeking is considered a coping strategy for personal growth, as it concerns the active efforts made by individuals to implement their skills or acquire new ones (Chen et al. 2022). These results are in line with the literature about stress management and age. Several studies, in fact, highlighted how ageing is positively related to the development of coping strategies related to stress management. A study carried out during the pandemic (Ghislieri et al. 2023), showed that older students are less exhausted and more engaged than their colleagues younger, so they seem to be able to recover resources useful to build their own academic and professional paths.

So, two interpretations are proposed: one evolutionary and the other contextual. The evolutionary interpretation argues that maturation processes influence coping strategies, these being intrinsic factors not related to environmental factors.

The contextual interpretation, on the other hand, suggests that differences in coping strategies result from the changes that people face. In other words, most of the differences can be explained by differences in the sources of stress that people face (Whitty 2003; Folkman et al. 1987).

With reference to this last conceptualisation, it can be deduced that individuals who are over the age of 22 are the same as those who have graduated with a bachelor's degree and are in the process of drawing up a life project that will support decision-making about their academic and/or working future. In this sense, the search for challenges appears to be a search for opportunities for development and growth, a necessary tool for building one's life purpose.

## 5 Conclusion

This study started from the perspective of the Job Demand Resource Model (JD-R) (Lewig et al. 2007), the model maintaining its validity, has been converted from a work to a higher educational context. The seeking of challenges during academic life effectively had a positive and significant impact on academic performance. Students that seek challenges and new projects can influence the environment actively and transform current situations into favourable ones (Bateman and Crant 1993) and cope better with new challenges deriving from new work environments and deal more successfully with uncertain global economy (Cilliers et al. 2018; Molino et al. 2020).

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 outcome 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 in critical and ordinary moments (e.g., those operating in colleges and universities). This could have different practical implications, and a considerable impact, on personal and social well-being: indeed, measuring life crafting could be useful for both research and human resources management but also for counselling 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.

### 5.1 Limitations and further direction of research

Since life crafting is a self-driven strategy to produce meaning, a self-report evaluation changing over time could be necessary, under individual and organizational variables. In other words, a longitudinal study could guarantee a higher quality in the construct evaluation.

Furthermore, self-report measures can be a limitation. Self-report measures can determine positive bias, underlying a dependence on the own personal opinion (social desirability). Objective indicators, such as job performance or physical variables of mental health, should be considered in future.

In anticipation of further studies, the validity will be extended taking into account the external variables in relation to life crafting

In the end, life crafting can differ in function of demographic and social variables, such as age, gender, educational level, and geographical context: for example, taking into account the North or South of Italy may represent a crucial difference in terms of the labor market, job opportunities and social services. Future research should consider specific geographical contexts, but also different types of participants (such as workers), analyzing objective variables such as career counseling agencies, free services to manage work-life balance, and social and career counseling programs to support people with special needs. Future studies should consider these variables to develop and propose social local actions to improve people's social and working life.

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**Data availability** The datasets analyzed during the current study are not publicly available due to the confidential nature of the collected data but are available from the corresponding author on reasonable request.

## Declarations

**Conflict of interest** On behalf of all authors, the corresponding author states that there is no conflict of interest.

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