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PARTIAL LEAST SQUARE PATH MODELLING AND MAXIMUM ENTROPY FOR THE STUDY OF ENTREPRENEURSHIP EDUCATION IN NAPLES UNIVERSITY

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SUMMARY

Although successful entrepreneurship education (EE) is possible through the most effective way to manage teachable skills and competencies, there is no universal pedagogical recipe to teach entrepreneurship. This paper attempts to identify the most appropriate teaching methods and addresses the paucity of entrepreneurial outcomes on university experiences in EE. Using a survey of students at a Naples University, it attempts to advance our understanding of an entrepreneurship education program. The study is based on a sample of 665 students and the analysis has been carried out considering joint use of Partial Least squares-path modelling (PLS-PM) and the Generalized Maximum Entropy Estimator (GME). The results show that the entrepreneurial outcome of Entrepreneurship Education programmes is influenced on the satisfaction that students perceive from the educational process. The novel aspects of this paper are: the formalization of an entrepreneurship education program in a Naples University and a methodological point of view involving integration between PLS-PM and GME estimators through PLS reliability measures.

Keywords: *Partial Least squares Path Modelling, Generalized Maximum Entropy, Entrepreneurship Education Programs, Entrepreneurial Outcomes.*
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1. INTRODUCTION

Entrepreneurship education continues to grow and develop worldwide. As affirmed by other authors, the scope of entrepreneurship education has broadened, rapidly spreading across disciplines in university settings and permeating different levels

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within educational systems (Neck and Greene, 2011; Morris, Kuratko and Cornwell, 2013; Fox, Pittaway and Uzuegbunam, 2018). Despite this landscape of increasing demand and diversification, the intellectual foundations of educational practice have no universal pedagogical recipe to teach entrepreneurship (Pittaway and Cope, 2007b; Loi, Castriotta and Di Guardo, 2016). There is a void between current theoretical understanding of the entrepreneurship process as it applies to opportunity recognition, evaluation, and exploitation, and its simulation in educational practice (Fayolle, Verzat and Wapshott, 2016; Fox *et al.,* 2018).

Education is the key to national development because it facilitates economic growth and provides the basis for improving the quality of life, and is also an essential sustainability tool. Thus, the present global economic crises suggest that the entire world is involved in a war between financial/qualitative education and catastrophe (Aluwong, 2010).

An Entrepreneurship Education Program (EEP) would involve acquisition of the skills, ideas and management abilities necessary for job creation. As an entrepreneur promotes employment rather than seeking employment, it is necessary to embrace this type of education and provide all the required resources to make it functional.

Entrepreneurship education could be used as a tool for fighting poverty and unemployment in Italy. Education is said to be qualitative when the input, represented by students, teachers, finances, facilities and equipment, are converted together through teaching and learning (including both theoretical and practical tasks), and consequently produce a desirable output. The output elements are then better equipped to serve themselves and society. The quality of input influences the quality of output to a large extent. In other words, the quality of entrepreneurship education on the input elements, such as teachers, students and infrastructural facilities will greatly influence the input relative to the output (Olorunmolu, 2010).

According to ISTAT (2018) data, the youth unemployment rate is growing: in July it stood at 35.5%, up 0.3 points from June, and Entrepreneurship Education could have played a vital role in equipping aspiring entrepreneurs with the necessary intellectual capacity, skills and suitable work habits, along with attitudes to enable job creation to facilitate growth within the Italian economy.

Entrepreneurship education and the learning process are seen as fundamental to developing an entrepreneurial culture, however, teach and learn entrepreneurship includes so many different dimensions, e.g. environmental factors, personal relations between potential and established entrepreneurs and their network, development of one's entrepreneurial behaviour and personality, and of course, the learning process itself (Kaseorg, Raudsaar and Uba, 2010; Iscaro, Castaldi, Sepe and Turi, 2018).

The existence of a supportive entrepreneurial culture in the region, indicated by higher levels of social acceptance of entrepreneurship and accessible role models, will positively influence the effect of human capital on growth aspirations (Capelleras, Contin-Pilart, Larraza-Kintana and Martin-Sanchez, 2019).

Other authors demonstrate this and explain how regional social legitimacy influences the relationships between individual entrepreneurial beliefs, intentions and start-up behaviour (Kibler, Kautonen and Fink, 2014).

This is quite unlike the entrepreneurial method that refers to how entrepreneurs go about solving problems as they create new markets and opportunities (Sarasvathy and Venkataraman, 2011).

In line with Fayolle's position (Fayolle, 2013; Verzat, 2015) that proposes three research orientations, in this discussion we attempt to consider the extent to which current educational practices in the field of entrepreneurship are consistent with current understanding of the entrepreneurial process, and associated skills and competencies.

The novel aspects of this paper are therefore: (*i*) the formalization of an entrepreneurship education program in Naples University; (*ii*) the integration between PLS-PM and GME estimators through PLS reliability measures in order to improve the estimation of path coefficients in a GME approach.

The paper is structured as follows: in Section 2 the literature review in entrepreneurship education, entrepreneurial outcomes and the theoretical framework are shown. In Section 3 the research hypotheses are analysed. In Section 4, the research methodology to evaluate the effectiveness of the entrepreneurship education program, the sample and measures, are explained. In Section 5, the results are analysed. Finally, we draw conclusions and discuss some major implications for future research in Section 6.

2. LITERATURE REVIEW

2.1 *Current educational practices in the field of entrepreneurship education*

The purpose of this article is to consider the extent to which current educational practices in the field of entrepreneurship are consistent with actual understanding of the entrepreneurial process, associated skills, and competencies (Fox *et al.*, 2018).

The study of entrepreneurship has advanced significantly, showing greater research breadth, depth and rigor. The most common reason why researchers and experts promote Entrepreneurship Education is that entrepreneurship is seen as a major engine for economic growth and job creation (Maina, 2014).

Entrepreneurship education can be defined broadly as ''any pedagogical program or process of education for entrepreneurial attitudes and skills'' (Fayolle and Lassas-Clerc, 2007).

There is an on-going debate within entrepreneurship pedagogy about the merits of theory versus practice, and both perspectives are focused on increasing student interest in starting a business. Unfortunately, this emphasis has led some to conclude that current approaches to entrepreneurship education fall short, as there is limited evidence that entrepreneurship education actually leads to new venture creation (Yamakawa, McKone-Sweet, Hunt and Greenberg, 2016).

To help students develop an entrepreneurial mind-set, entrepreneurial educators need to move beyond merely teaching students the concepts and skills, and to consider an often-overlooked element of entrepreneurship and entrepreneurship pedagogy, namely, the entrepreneurial method (Yamakawa *et al.,* 2016).

The term ''entrepreneurial method'' refers to how entrepreneurs go about solving problems as they create new markets and opportunities (Sarasvathy and Venkataraman, 2011). While this method is defined as ''a logic that can be taught and learned by an increasing variety of individuals'', (Sarasvathy and Venkataraman, 2011), few entrepreneurship curricula have begun to focus on teaching this particular problem solving method.

Fayolle and Gailly (2008) argue that there is a lack of a precise definition of entrepreneurship as a teaching field, so the philosophical conceptions about teaching, the role of the teacher, and the role of the students should be clarified in each course. Similarly, Rahman, Adedeji, Uddin and Rahaman (2017) sustain that as yet there are no guidelines for selecting the teaching methods that might engage a particular group of students in order to disseminate the required body of entrepreneurship knowledge and generate a basis for learning in the near future.

Several systematic reviews of the literature have been published (Pittaway and Cope, 2007; Mwasalwiba, 2010; Li Ge and Xu-mei Peng, 2012; Fayolle, 2013; Byrne, Fayolle and Toutain, 2014) leading to different findings.

Fayolle (Fayolle, 2013; Verzat, 2015) proposes three research orientations for regarding the teaching methods and approaches that are adapted to types of learners and expected outcomes or what contextual factors contribute to increased effectiveness in entrepreneurship education: firstly; focusing on specific concepts and processes; secondly; crossing the disciplinary borders of entrepreneurship to tap into the theories and methods of education science and thirdly, developing reflexive knowledge of two key elements of Béchard and Grégoire's model (Béchard and Grégoire, 2009): the pedagogical practice adopted more or less consciously by the teacher and the factors in the institutional context that make this practice possible (Fayolle *et al.,* 2016).

In this perspective, educators must identify the conditions and factors that will allow them to maintain good control of every programme implementation.

2.2 *Entrepreneurial Outcomes*

Entrepreneurship is as much about the change and learning that the individual entrepreneur experiences by interacting with the environment as about the change and value creation the entrepreneur causes through his/her actions. Learning and value creation are thus seen as the two main aspects of entrepreneurship. This view aligns better with the learning-focused aims of educational institutions than many other entrepreneurship definitions.

Entrepreneurs have introduced new technologies that have spawned countless industries, creating jobs and improving the social and economic conditions of nations (McMullen and Warnick, 2015). Entrepreneurship has also improved the quality of life (McMullen and Warnick, 2015). It is the engine that moves and sustains capitalism, and is universally accepted as a means of creating momentum for growth in developed, emerging and less developed economies.

This article seeks to expand knowledge and understanding of educational practice in entrepreneurship by focusing on alternative methods of analysis, in order to contribute to an entrepreneurial outcome.

Interestingly, most business schools appear to use a combination of theoretical and practical approaches, often reinforced by detailed analysis of entrepreneurial problems and solutions grounded within ‘‘realistic’’ cases and field studies (Peterman and Kennedy, 2003).

The research shows that the learner-entrepreneurs seems confused, and need to determine which program will fit their needs as well as those of their stakeholders (Bischoff, Volkmann and, Audretsch, 2018; Steiner, Brock Pittz and Liguori, 2018; Kariv, Matlay, Fayolle, 2019). In a context characterized by such a high heterogeneity and variety of entrepreneurship programmes, well-defined entrepreneurial learning outcomes are needed for educators to adopt effective entrepreneurial learning methodologies.

The study of entrepreneurship education and training highlighted to consider practice perspectives, i.e. the Entrepreneurial outcomes to improve understanding of how measurement and research design (Newman, Obschonka, Schwarz, Cohen and Nielsen, 2019).

While no consensus has been established on a definitive method for measuring EE outcomes (OECD 2009), any study of entrepreneurship education training programmes must clarify which outcomes are being measured, and how they are being measured. Drawing upon the available literature and the evaluations of a range of entrepreneurship education training programmes where outcomes vary widely (Matlay, 2008; Solomon and Matlay, 2008; Nweman *et al.,* 2019), this work attempts to evaluate the entrepreneurial outcome of a university entrepreneurship education programme with appropriate statistical models using data from a recent survey.

In particular, the empirical study illustrated in this work was conducted on a sample of university students. The sample students filled in a single questionnaire, distributed on two separate occasions: between February and June 2017 and between September and February 2018.

Although aware of the various questionnaires used in the field (Gruber-Muecke and Kailer, 2015; Ruskovaara, Pihkala, Seikkula-Leino and Rytkölä, 2015), we structured the questionnaire using the European Union (European Commission 2013) entrepreneurship education guidelines , which are based on a conceptual model (see Figure 1) where the dimensions ‘‘comprehensibility of EEP (CEEP)’’, ‘‘transparency in program exposure (TPE)’’, ‘‘skills to develop business ideas (SDBI)’’, and ‘‘support activity (SA)’’ describe the entrepreneurship education program (EEP).

The theory of effectuation (TE) states that entrepreneurs will determine goals according to the resources in their possession and it offers alternative views on how entrepreneurs think, make decisions, behave and act entrepreneurially (Sarasvathy, 2001). The dimension educational outcome (EO) indicates the utility of the practice in addition to the theory for entrepreneurship education in terms of acquisition of entrepreneurial competencies.

3. RESEARCH HYPOTHESIS

Based on affirmations made in previous, it could be hypothesised that the structure of the Entrepreneurship Education Program supports the acquisition of skills and competencies by students and reveals educational effectiveness by means of a programme that stimulates students (Figure 1).

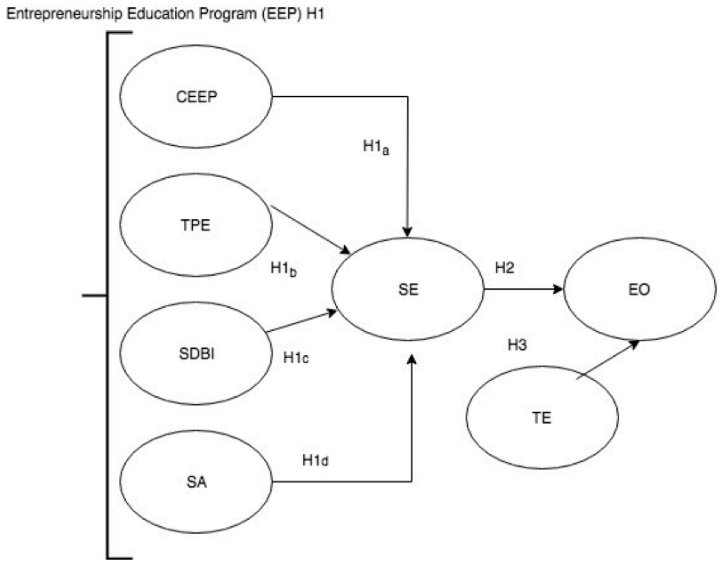

FIGURE 1. - *Conceptual Model in Entrepreneurship Education Program*

In this perspective, as illustrated in the conceptual model (Figure 1), we suggest the following research hypotheses:

- H_1: The Entrepreneurship Education Program (EEP) impacts positively on student evaluation SE.
  In particular:
- H_{1a}: CEEP impacts positively on SE;
- H_{1b}: TPE impacts positively on SE;
- H_{1c}: SDBI impacts positively on SE;
- H_{1d}: SA impacts positively on SE.
- H_2: The evaluation generated by students positively impacts educational outcome EO in terms of the effectiveness of the programme.
- H_3: TE impacts positively EO.

4. METHODOLOGY

4.1 *The sample*

The study involved 665 first-year master degree economics students from the public universities of Campania, with a sampling error of 4.5% and a significance level of 95%.

The graduates involved in the study received a questionnaire on the relationship between theory and practice in entrepreneurship education during the course. The questionnaires were administered at two different times: between February and June 2017 and between September and February 2018.

We carried out a stratified sampling regarding department of economics, degree classes and gender.

4.2 *Measures*

Data was collected by using a questionnaire structured into seven different dimensions (or latent variables), CEEP, TPE, SDBI, SA, SE, TE, made up of items (or manifest variables) measured on a Likert scale from 1 to 7 (where 1 was the lowest score and 7 the highest). In particular, there are three questions on the global satisfaction of the students about the Entrepreneurship Education Program that represent the latent variable called Student Evaluation (SE).

The latent variables (LV) and the corresponding manifest variables (MVs) are shown in Table 1.

Before data analysis, pre-processing was performed in order to improve the mathematical properties of the Likert scale, transforming the data collected from ordinal into a quasi-cardinal scale.

The method used is based on the Thurstone approach (Zanella, 2001), the main idea of which is that the criterion regarding the choice of each respondent follows a *normal distribution*. Following this idea, it is possible to transform the original ordinal scale to a scale that has a Normal distribution metric.

4.3 *PLS-PM*

The PLS estimation method was first formalized by Herman Wold (1973), for use in multivariate analyses. The application in Structural Equation Modelling (SEM) was again developed by Wold (1975) and the main references on the PLS algorithm are from Wold (1982).

The main idea of PLS for the structural equation models is an iterative combination of path analysis to give a measure of the relationships among the theoretical constructs (Structural Model or Inner Model (1)), then factorial analysis for measuring the latent construct (Measurement Model or Outer Model (2)):

$$\boldsymbol{\xi}_{(m,1)} = \mathbf{B}_{(m,m)} \cdot \boldsymbol{\xi}_{(m,1)} + \boldsymbol{\tau}_{(m,1)} \tag{1}$$

$$\mathbf{X}_{(q,1)} = \boldsymbol{\Lambda}_{(q,m)} \cdot \boldsymbol{\xi}_{(m,1)} + \boldsymbol{\delta}_{(q,1)} \tag{2}$$

In the Structural Model (1) $\boldsymbol{\xi}$ is the vector of the m latent variables and **B** is the path coefficients matrix, with zeros on its diagonal representing the causal effect among the LV.

The Measurement Model (2) contains the **x** vector of the q MV and the coeffi-

TABLE 1. - *Latent and manifest variables*

Latent Variables	Manifest Variables
CEEP	CEEP1 CEEP2 CEEP3 CEEP4 CEEP5 CEEP6
TPE	TPE1 TPE2 TPE3 TPE4
SDBI	SDBI1 SDBI2 SDBI3 SDBI4
SA	SA1 SA2 SE3
SE	SE1 SE2 SE3
TE	TE1 TE2 TE3
EO	EO1 EO2 EO3 EO4 EO5 EO6 EO7 EO8 EO9 EO10

cient matrices $\boldsymbol{\Lambda}$ of the relationships between the latent constructs and the observed variables. The vectors **t** and **d** are the structural and the measurement error vectors and the $\boldsymbol{\Psi}$ and $\boldsymbol{\Theta}^{\boldsymbol{\delta}}$ are the diagonal matrix variance of the structural error term t and the measurement error term $\boldsymbol{\delta}$ respectively.

For the parameter estimations, the PLS algorithm (Wold, 1982; Tenenhaus, Esposito Vinzi, Chatelin and Lauro 2005) considers two double approximations for the latent variables ξ_j:

- *external estimation*, called y_j, obtained as the product between the block of MV X_j, the *j*th latent variable ξ_j , and the so called *outer weights* w_j. The outer weights w_j represent the estimations of measurement model coefficients (Λ), which may have two kinds of relationship with their LV: a reflective relationship or a formative relationship. The reflective relationship assumes that the MV are a reflection of the latent constructs, following the approach of factorial analysis, while the formative relationship assumes that the observed variables form the latent constructs.
- *internal estimation*, called z_j, obtained as product between the external estimation y_j and the so-called *inner weights* e_{ji}. The inner weights $e_{ji,}$ are defined through the correlation between y_j and the connected y_i, with $i \neq j$.

The PLS algorithm starts by initialising outer weights to one for the first manifest variable of cach latent variable; the parameter estimation is then performed until convergence is achieved by iteratively computing:

– *external estimation*, $y_j = X_j\, w_j$;
– *internal estimation*, $z_j = \Sigma_{j \neq i}\, e_{ji}\, y_j$;
– *outer weights estimation*.

The causal paths among LV are obtained through the ordinary least squares (OLS) method or PLS regression.

To estimate the parameter of the model, we used the module R-package.

4.4 *GME estimator*

The GME estimator was developed by Golan, Judge and Karp (1996) to overcome some of the limits of traditional methods as distributional assumptions or ill-posed problems. GME is an extension of the Maximum Entropy Principle proposed by Jaynes (1957) and based on Shannon's entropy index.

In this study we propose to use the property of the GME estimator to improve the inner estimation of the PLS-PM introduced in the previous, and we describe the GME rationale for doing so.

Let us consider the following linear regression model for the i^{th} unit:

$$y_i = \alpha + \Sigma_{j=1}^{m} x_{ij}\beta_j + \varepsilon_i \quad i = 1, \ldots, n \tag{3}$$

where n is the number of observations and m the number of independent variables.

The GME estimator is outlined by reformulating the parameters (α and β) and the error term (ε_i) as the expected value of some discrete random variables Z^α, Z^β, Z^ε, as follows:

$$y_i = \left(\Sigma_{k=1}^{K} Z_k^\alpha p_k^\alpha\right) + \Sigma_{j=1}^{m} x_{ij}\left(\Sigma_{k=1}^{K} Z_{jk}^\beta p_{jk}^\beta\right) + \left(\Sigma_{h=1}^{H} Z_{ih}^\varepsilon p_{ih}^\varepsilon\right) \quad (4)$$

The discrete random variables are usually composed of three or five support points, symmetrical around zero, with the associated probability distributions $\mathbf{p} = (\mathbf{p}^\alpha, \mathbf{p}^\beta, \mathbf{p}^\varepsilon)$ which assume a value in the interval (0, 1) and respect the following normalization constraints:

$$\Sigma_{k=1}^{K} p_k^\alpha = 1; \;\; \Sigma_{k=1}^{K} p_{jk}^\beta = 1; \;\; j = 1, \ldots, \; m; \; \Sigma_{h=1}^{H} p_{ih}^\varepsilon = 1; \;\; i = 1, \ldots, n \quad (5)$$

The idea underlying the GME method is to estimate the unknown parameters and the error terms by maximizing the following Shannon entropy function:

$$max\{H(\mathbf{p})\} = -\Sigma_{k=1}^{K} p_k^\alpha ln \; p_k^\alpha - \Sigma_{j=1}^{m} \Sigma_{k=1}^{K} p_{jk}^\beta \ln p_{jk}^\beta - \Sigma_{i=1}^{n} \Sigma_{h=1}^{H} p_{ih}^\varepsilon \ln p_{ih}^\varepsilon \quad (6)$$

subject to the data constraints (consistency constraint) represented by the re-written model in (4) and the normalization constraints given by (5). For further in-depth discussion see Golan *et al.,* (1996).

In the GME context an important role is played by the discrete random variables Z^α, Z^β, Z^ε, since the choice of their values affect the estimation results. These variables represent the empirical knowledge of the analysed data. In case no conceptual or empirical knowledge exists, the range of Z^α, Z^β is specified as symmetrical around zero with large bounds (e.g. [-100 0 100]), while the Z^ε can reflect the sample variability, for instance, by using the three-sigma-rule (e.g. [-3s_y 0 3s_y]) (Pukelsheim, 1994).

In our study we will integrate the information on the reliability of the estimated latent variable by considering Cronbach's alpha as prior information on the error variability.

As stated in the introduction, in the second step of the analysis we specify the relations between the LV in the structural model using GME, and take the measurement errors obtained from the previous step into account, without any distributional error assumptions (Ciavolino and Al-Nasser, 2009; Carpita and Ciavolino, 2017; Angelelli, Ciavolino and Pasca, 2019; Corallo, Fortunato, Massafra, Pasca, Angelelli, Hobbs and Ciavolino, 2019).

5. ESTIMATION RESULTS

5.1 *PLS-PM Results: Outer Model*

The outer model establishes the relationship between the MV block and their corresponding LV. In particular, in the first step the structural equation model involved 33 MV on seven LV. Based on the communality values, some variables have been eliminated due to their having low communality values, namely, the level of collaboration with medium-large companies, higher expectations, and an increase in risk propensity.

The unidimensionality of the reflective MV block was checked by means of Dillon-Goldstein's rho (Wertz, Linn and Jöreskog, 1974). According to Chin (1998), Dillon-Goldenstein's rho is considered a better indicator than Cronbach's alpha, as it is based on the model results, (i.e. the loadings), rather than on the correlations observed between the MV in a dataset. A block is unidimensional if this index is > 0.7. The value of the index is > 0.7 for all the observed MV blocks.

On the contrary, the inner model considers the relationships between LV, which are assumed to be linearly interconnected according to a causal-effect relationship model.

The present study aims at verifying the existence of positive significant relationships between the following LV from an explorative and non-confirmative point of view:

1. Comprehensibility and student evaluation
2. Transparency in program exposure and student evaluation
3. Skills to develop business ideas and student evaluation
4. Support Activity and student evaluation
5. Student evaluation and Educational outcome
6. Theory of effectuation and Educational outcome

In correspondence with the dependent LV (student evaluation and Educational outcome), we read the coefficient of determination R^2. Following Sanchéz, Trinchera, Russolillo (2015), we have a moderate R^2 for the ''evaluation'' latent variable (0,557), and high R^2 for the ''Educational outcome'' latent variable (0,653).

Moreover, we also consider the GOF (Goodness of Fit index) in order to evaluate the goodness of the whole model. The GOF is a global criterion proposed by Tenenhaus, Amato and Esposito Vinzi (2004) to account for the model performance in both the measurement and the structural model, and thus provide a single measure for the overall prediction performance of the model. In this paper, the GOF value is equal to 0.62.

In Table 2 we show the bootstrap results for the Outer Model. In particular, the loadings will have values all positive and significant (T-statistic are all greater than 2).

5.2 *GME Results: Inner Model*

In this sectionSection we consider the estimates of the outer model in PLS path modelling, in order to obtain the estimate of standard error and T-statistics for path coefficients in GME. The GME structural model estimates are more reliable than PLS-PM, especially where multicollinearity is present (Golan *et al*., 1996; Ciavolino and Al-Nasser, 2009).

TABLE 2. - *Bootstrap Validation for loading coefficients*

Variables	Original	Mean. Boot	Std. Error	T-Statistics
CEEP1	0.795	0.797	0.0476	16.70168067
CEEP2	0.824	0.785	0.0475	17.34736842
CEEP3	0.882	0.864	0.0191	46.17801047
CEEP4	0.801	0.795	0.0479	16.7223382
CEEP5	0.722	0.729	0.0547	13.19926874
CEEP6	0.582	0.593	0.0722	8.060941828
TPE1	0.857	0.855	0.0347	24.69740634
TPE2	0.893	0.893	0.0201	44.4278607
TPE3	0.84	0.843	0.0311	27.0096463
TPE4	0.917	0.919	0.0161	56.95652174
SDBI1	0.914	0.913	0.0173	52.83236994
SDBI2	0.902	0.911	0.0181	49.83425414
SDBI3	0.868	0.871	0.0307	28.27361564
SDBI4	0.71	0.708	0.0891	7.968574635
SA1	0.755	0.746	0.0935	8.07486631
SA2	0.747	0.736	0.0871	8.576349024
SA3	0.668	0.662	0.0915	7.300546448
TE1	0.866	0.861	0.0466	18.58369099
TE2	0.768	0.762	0.0935	8.213903743
TE3	0.881	0.884	0.0265	33.24528302
SE1	0.926	0.925	0.0133	69.62406015
SE2	0.885	0.872	0.0349	25.35816619
SE3	0.86	0.856	0.0397	21.66246851
EO1	0.784	0.782	0.0463	16.93304536
EO2	0.739	0.734	0.0563	13.12611012
EO3	0.613	0.601	0.1048	5.849236641
EO4	0.671	0.655	0.0721	9.306518724
EO5	0.686	0.688	0.0597	11.49078727
EO6	0.818	0.819	0.0352	23.23863636
EO7	0.876	0.866	0.0357	24.53781513
EO8	0.848	0.838	0.0406	20.88669951
EO9	0.489	0.479	0.0904	5.409292035
EO10	0.729	0.735	0.0637	11.44427002

To evaluate the presence of multicollinearity in our data we use several diagnostic measures, as reported in Table 3. In particular we have considered the VIF value and CVIF Klein, which all confirm the presence of collinearity among the estimated LV.

TABLE 3. - *Index for multicollinearity validation*

	VIF	**TOL**	**Wi**	**Fi**	**Leamer**	**CVIF Klein**
CEEP	22.800	0.4386	524.799	793.599	0.6623 - 3.3208	1
TPE	29.559	0.3383	801.899	1.212.628	0.5816 - 4.3051	1
SDBI	26.955	0.3710	695.163	1.051.223	0.6091 - 3.9259	1
SA	13.944	0.7172	161.694	244.513	0.8469 - 2.0309	0

1 –> COLLINEARITY is detected by the test;
0 –> COLLINEARITY is not detected by the test.

The integration between PLS-PM and the GME Estimator is achieved by choosing suitable support points for the discrete random variable $\mathbf{Z}^{\varepsilon}$ in such a way as to reflect the latent variable reliability. The idea is to transfer the information relative to the measurement model to the structural model by properly designing the magnitude of the error terms with the three-sigma-rule (e.g. [-3s_{ξ} 0 3s_{ξ}]).

As standard deviation for the LV SE and EO, we used the reliability indexes alpha estimated by PLS-PM, which represent the variance explained by the LVs for each MV. As reported in Table 4, the standard errors s_{ξ} for each latent variable, are estimated as $(1 - \text{alpha})^{1/2}$. In this way the path coefficients will be estimated by taking the latent variable measurement errors into account, thereby improving the obtained estimates (Table 4).

TABLE 4. - *Alpha and support point definition*

LV	**Alpha**	**se =** $^{1\backslash 2}\ (1 - alpha)$
SE	0.864	0.368
EO	0.871	0.359

Finally, the full specification of the Inner model with the GME estimates (Path coefficient, Standard Error and T-Statistics) is shown in Figure 2.

Considering the research hypotheses mentioned in Section 2.2, we affirm that: H1c, H1d, H2, H3 are confirmed, while there is no evidence supporting H1a and H1b (no significant link at 5%).

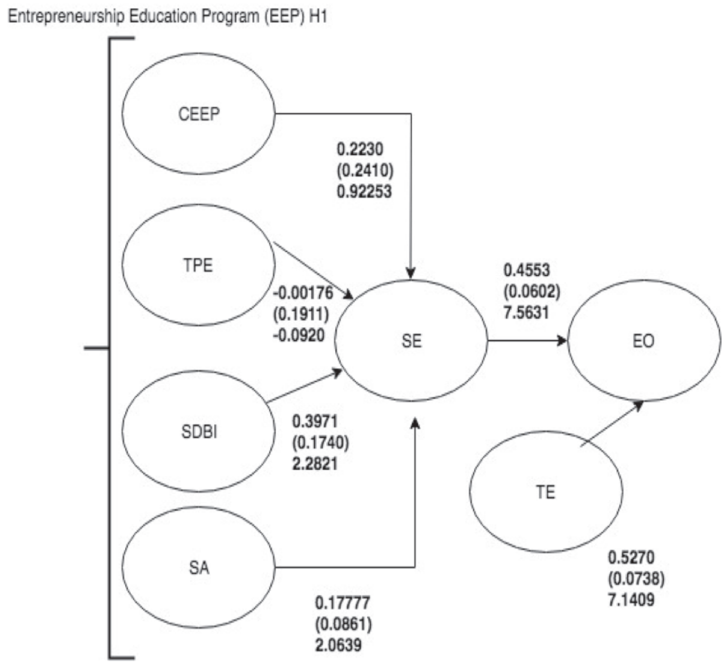

FIGURE 2. - *Estimated model with the GME-SEM. Path coefficient, Standard error and T-statistics*

6. DISCUSSION AND CONCLUSIONS

The Entrepreneurship Education Program plays a vital role in the social, political and economic development of any nation. This is possible when jobs are created for the population by establishing a lot of businesses that will accommodate the unemployed youth in Italy. A qualified entrepreneurship education graduate would have acquired enough skills relevant to the management of small business.

This study spurs research in the field of entrepreneurship education programs, a relatively immature discipline compared to other business, economic and social research disciplines, and draws attention to the entrepreneurial outcome where it lacks both large-scale research methods and complex models that provide a foundational, empirical base, partly due to the resource-intensive nature of such studies.

Positive impacts emerge from the analysed latent factors data providing enhanced quality of life to entrepreneurs, employees, customers, and the community.

In this perspective, it increases the interest in entrepreneurship education expressed time and again by politicians, higher education institutions, universities and students. Entrepreneurship education actively contributes both to the development of student ''entrepreneurs'' and to the entrepreneurial activity of universities. Although the findings are not entirely conclusive, they are in line with those who claim that entrepreneurial capabilities are not inborn, and as such, entrepreneurship can be learned.

This study represents a first step in developing teaching of the entrepreneurial method within the universities.

The results of this paper allow us to affirm that entrepreneurship is primarily learned by experience and discovery, and that entrepreneurial learning should be conceived as a process whereby knowledge is continuously shaped and revised as the result of new experiences.

The second novel aspect was the combination of PLS-PM and GME estimators, by taking into account the PLS reliability measures and improve the estimation of path coefficients with the GME estimator.

In this way we combined the statistical properties of both estimators, from one side the multidimensional definition of the model through mean PLS, while in the second step the GME simultaneously integrated the scale reliability information and dealt with multi-collinearity.

We expect to analyse new data in future research, particularly by evaluating the entrepreneurship education program over time by means of a longitudinal model.

Moreover, other approaches could be extended in various ways, such as considering correlation design between latent variables in the structural part of the model, or using the GME directly in the PLS estimation procedure.

Finally, in future research it would be appropriate to analyse how the considered latent factors directly affect the quality of life.

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