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Corporate reputation and intellectual capital formation

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Abstract: *- The Meta -analyses reveal the factors that during a period have influenced the behavior of a formal sector such as Higher Education Institutions. The objective of this work was to establish fixed effects models to explain the influence of diffuse variables in capital formation. Intellectual, considering contextual, educational, academic and professional variables. A retrospective study was carried out with literature from 2019 to 2022, considering the incidence of contextual, institutional and subjective factors in academic training. A risk threshold was found in which formation is determined by homogeneous random effects. That is, academic training depends on the relationships between factors that the literature has reported in the last three years. In relation to the state of the art, it is recommended to extend the review in order to be able to anticipate diffuse scenarios.*

Keywords: *- Capital, intellectual, formation, diffuse, meta-analysis*

I. Introduction

In the social sciences, fixed effects meta -analytical models have gained special relevance due to their ability to predict a scenario, context and process, although they have focused on the estimation and prediction of simple variables, avoiding the effects of diffuse variables such as emerging ones. in training and research processes (García, 2020). In the sciences of complexity, the analysis of fuzzy logic has been used to observe the emergence of emerging entities such as university governance in which new actors seem to define the quality of academic processes and products, such as managers, producers and knowledge transfers (Sánchez et al., 2019) .

Fuzzy logic is due to mathematical and computational algorithms applied to the orientation of aerospace or vehicular technologies to face the imponderables of air or land traffic, avoiding coalitions and facilitating the movement of people or goods (Molina, Martinez & Garcia, 2019). In educational and behavioral sciences, fuzzy logic has been used to address emerging issues such as corporate reputation (García, 2021). It is estimated that in the last three years, new jobs are related to new skills such as comprehensive data analysis (García et al., 2017). The self-concept of an institution regarding its academic training is linked To professional and labor training, even when the distance between the educational curricula and the demands of the labor market are distant.

In that tenor, the investigation; the management, production and transfer of knowledge have been involved in complex, random and diffuse processes that affect the formation of human capital in general and intellectual capital (Garcia, 2020). For this reason, a systematic review of the educational, academic, scientific and technological systems is necessary to establish training, education and training paths for those interested (Carreón, Hernández & García, 2019) . Systematic reviews and Meta -analyses have shown that factors are grouped into determinants of behavior as long as their relationships are systematic (Carreón et al., 2020). In this sense, the emergence of corporate reputation can be meta-analyzed as a factor that the literature had not addressed, but whose random and heterogeneous effects can reveal it as an axis of academic training.

However, traditional fuzzy logic studies have been built from disturbances, contingencies and disturbances in which the gradients (corruption, catastrophes, collisions) are fuzzy determinants of the distribution of the population, its capacities and resources (Carreón, Espinoza & Garcia, 2019).

Fuzzy logic studies have not established the relationship of homogeneous random effects and have not inferred the emergence of new determinants of behavior.

In the case of the social sciences, fuzzy logic models warn of the emergence of actors such as the cases of managers, producers and disseminators of knowledge who, in interrelation with repositories and technologies, make up the metrics of the quality of the processes and scientific and technological knowledge. Products of institutions in alliances with knowledge-creating organizations (Sánchez et al., 2019). In this sense, academic training is no longer just collateral to corporate reputation as indicators of fuzzy logic (García et al., 2022). In addition, academic training is a process that reveals corporate reputation considering the relationship with its determinants.

Budsankon et al., (2015) carried out a systematic review of the studies that brought effects of the environment on analytical, critical and creative thinking skills, establishing as predictors that the classroom environment and intellectual skills explain 96% of the variance total. That is, the emergence of corporate reputation is less likely to emerge than academic training, but it is possible to infer from a systematic and meta-analytic review if this relationship persists in other similar studies during an observation period.

Payborji & Haghighi (2016) carried out a meta-analysis on the total effects of intellectual capital management on the productivity of companies, finding a positive and significant relationship between management with respect to knowledge production, profitability and reputation. Corporate. .The research explained the emergence of indicators of a fuzzy logic in academic training, but the study design was aimed at demonstrating the random effects of factors stated in the literature rather than the appreciation of random and heterogeneous events.

Basyith (2016) found in his review that a high percentage of Indonesian companies are family-owned, consequently, such a situation would be expected to influence the profitability of companies by not having an intellectual capital formation system, but the listing law. On the stock market by imposing hiring standards and the quality of employees, led to nepotism, affecting the hiring of talent. The fuzzy logic of family decisions could have been addressed from the Meta -analysis of those factors that generate trust, but nepotism or influence peddling clouded the analysis of the determinants of profitability.

In summary, the formation of intellectual capital ranges from traditionalist nepotism to transparency in the hiring of intellectual capital, measuring its performance from management in its academic, professional and labor training, as well as its consolidation encrypted in the conversion of intangible assets. By the degree of impact on the value of companies that create knowledge (Elizarraraz, 2020). From the fuzzy logic of academic training, knowledge networks that make possible the risk threshold reflected in an opaque or transparent curriculum, are concomitant to corporate reputation as long as it is derived from objectives, tasks and knowledge creation goals. .

It is precisely in this phase where the management, production and transfer of codified knowledge coincide in the formation of intellectual capital; professional service and labor practice established by alliances between institutions and knowledge-creating organizations (Espinoza 2020). A meta-analytic review of those institutional factors that allow the formation of intellectual capital will allow us to anticipate inhibition or facilitation scenarios that define a corporate reputation.

Therefore, the objective of this work will be to establish the dissipative trajectories of the investigative training process in order to be able to prospectively observe the decision-making of the managers, producers and diffusers of specialized and updated investigative knowledge as required by the indexing systems.

Are there significant differences between the fuzzy logic gradients related to academic training and corporate reputation reported in the literature with respect to the meta-analytic observations of the present work?

The premises that guide this work warn: 1) Corporate reputation and professional training can be explained from the fuzzy logic scale because they are emerging gradients of complexity; 2) The relationships between the variables suggest that the homogeneous random effects can be compared with the findings reported in the literature; 3) The risk threshold that allows interpreting the fuzzy logic scale and the meta-analysis of structural equations will allow testing the hypothesis; 4) The homogeneous random effects parameters will facilitate the understanding of the fuzzy relationships between the variables, as well as their structure.

II. Material and methods

This section presents the phased description of the risk and impact assessment methodology developed.

Phase I: Comprehensive Population Monitoring to determine management, production and transfer strategies. A direct follow-up was carried out, which gives a detailed population count and a measure of the works that are of interest for management, production and transfer, such as types of studies, paradigm, theory, model, construct and variables (see Table 1).

Table 1. Descriptive data studies

	Author	Literature	Phase	Division	Shows
2014	Hernandez et al.,	A	G	CSH	260
2015	Morales et al.,	A	P	CBI	230
2016	Ferr et al.,	D	G	CBS	220
2017	Garcia et al.,	A	P	CAD	200
2018	Sandoval et al.,	B.	D	CSH	220
2019	Carreon et al.,	A	D	CBI	240

A: Literature that reported total positive and significant effects of management on the production and transfer of knowledge; B: Literature that reported total positive and spurious effects of management in the production and transfer of knowledge; C: Literature that reported total zero effects of management on the production and transfer of knowledge; Literature that reported total negative effects of management on the production and transfer of knowledge. Phase M = Management Phase, Phase P = Production Phase. Phase D = Diffusion phase. BSI = Basic Sciences and Engineering, BHS = Biological and Health Sciences, SSH = Social Sciences and Humanities, SAD = Sciences and Arts for Design, NSE = Natural Sciences and Engineering, CDS = Communication Sciences and Design

Phase II: Identify threats that inhibit the formation of human capital. Perturbation gradients are identified from terminal efficiency classification, participation in academic events such as conferences, and scientific and technological production published in repositories such as Copernicus, Dialnet, Ebsco , Latinex , Publindex , Redalyc, Scieco , Scopus, WoS and Zenodo . This helps identify threats, areas of opportunity and competitive advantages.

Phase III: Formation of the Expert Evaluation Team (EA). The team includes 10 experts in management, production and information transfer. His responsibilities include: Scoring and grading of questionnaires; and opine to ensure the reliability of the data (see Table 2).

Table 2. Descriptives of expert judges in academic training and corporate reputation

Sex	Age	Scholarship	Discipline	Entry
Male	53	Doctorate	Psychology	37'213.00
Feminine	48	Doctorate	Sociology	29'435.00
Feminine	39	Doctorate	Pedagogy	33'214.00
Male	61	Post doctorate	Psychology	41'978.00
Male	55	Doctorate	Economy	40'781.00
Male	48	Post doctorate	Management	39'023.00
Feminine	38	Post doctorate	Psychology	28'961.00

Source: Prepared with study data

Phase IV: Determination of the impact of the risk. The phases to determine the impact of risk on the formation of human capital:

Phase 1: Identify t classes of threats and group them into j categories to obtain C_t^j, where C_t^jthe threats are in each category.

Phase 2: Score these C_t^jto get the threat influence score (〖SC〗_t^j) _ifor each t at each jy at each study site i . The EA team scores using a 5-point scale (High-5, Medium-3, and Low-1).

Phase 3: Calculation of threat influence weights (〖WC〗_t^j) _iusing the following sub-steps:

Phase 3.1 Comparison by fuzzy pairs of each one C_t^jby the EA team using the fuzzy scale (Table 1).

Phase 3.2: Conversion of fuzzy scale to triangular fuzzy number (TFN) a ̃_t= (a_1t,a_2t,a_3t)using 9-point fuzzy scale (Table 3). The triplet (a_1t,a_2t,a_3t)represents the lower, middle and upper TFN for threat t.

Table 3. Fuzzy 9-point scale.

fuzzy scale	Triangular Fuzzy Scale	Description
$\tilde{\mathbf{1}}$	(1,1,1) if diagonal (1,1,3) for equal importance	equal importance
$\tilde{\mathbf{3}}$	(1, 3, 5)	Moderate importance of one over the other
$\tilde{\mathbf{5}}$	(3, 5, 7)	Strong importance of one over the other.
$\tilde{\mathbf{7}}$	(5, 7, 9)	Very strong importance of one over the other.
$\tilde{\mathbf{9}}$	(7, 9, 9)	Extreme importance of one over the other
$\tilde{\mathbf{2}},\tilde{\mathbf{4}},\tilde{\mathbf{6}},\tilde{\mathbf{8}}$	(1, 2, 4), (2, 4, 6), (4, 6, 8), (6, 8, 9)	intermediate values

Step 3.3: Formation of the Fuzzy Decision Matrix by adding the scores of the team members using the equation

$$\tilde{v}_m = \left(\prod_{m=1}^{M} \tilde{a}_t \right)^{1/M} \quad \text{(one)}$$

Step 3.4: Compute the fuzzy decision weights (F ̃_t) using the equation

$$\tilde{F}_t = \left(\frac{v_{1t}}{\sum_{i=1}^{p} v_{3t}^{L}}, \frac{v_{2t}}{\sum_{i=1}^{p} v_{2t}}, \frac{v_{3t}}{\sum_{i=1}^{p} v_{1t}} \right) \quad \text{(two)}$$

Step 3.3: Calculation of the decision weights for the fuzzy decision weights using the equation

$$D_t = [\beta\ c_\alpha(F_{lt}) + (1-\beta)\ c_\alpha(F_{rt})],$$

$$0 \le \beta \le 1,\ 0 \le \alpha \le 1 \quad (3)$$

Where

$c_\alpha(F_{lt})=[(F_{2t}-F_{1t})\alpha+F_{1t}]$ Represents the left value of α-cut for $\tilde{F}_t$, and

$c_\alpha(F_{rt})=[F_{3t}-(F_{3t}-F_{2t})\alpha]$ Represents the correct value of α-cut for $\tilde{F}_t$.

Step 3.4: Determining Threat Influence Weights Using Normalization D_t

Table 4. Characteristics of the threat

moment of threat	Time Score (TS)	threat range	Rank Score (RS)	Severity of the threat	Severity score (SeS)
happening now	5	Entire population/area (>90%)	5	Rapid abandonment (> 30% in 1 year)	5
Likely in the short term (within 4 years)	3	Most of the population/area (50-90%)	3	Moderate dropout (10-30% per 1 year)	3
Likely long-term (more than 4 years)	one	Share of population/area (10-50%)	one	Slow churn (1-10% in 1 year)	one
Past (and unlikely to return) and no longer limiting	0	Few individuals/small area (<10%)	0	No seamless dropout (<1% in 1 year)	0

Step 4: Determining the site risk impact weights for the study sites using the equation (4)

Step 5: Score C_t^j according to their time, range and severity (Table 4) in relation to the probability that they "trigger" the mortality of the bird species in the study site i, to obtain Threat Activation Scores (Equation (5)). Scoring is done by members of the EA team. (5)

Step 6: Now rate the student and institution/organization subtypes against each other C_t^j to obtain the threat influence score for k students $(IC_t^j)_i^k$ and for l institution/organization subtypes $(IC_t^j)_i^l$., Medium-3 and Low-1).

Step 7: Calculate the total threat impact score $(TIC_t^j)_i^k$ using the equation

$$(TIC_t^j)_i^k = (IC_t^j)_i^k \times (TC_t^j)_i \quad (6)$$

And the total habitat threat impact score $(TIC_t^j)_i^l$ using the equation

$$(TIC_t^j)_i^l = (IC_t^j)_i^l \times (TC_t^j)_i \quad (7)$$

Step 8: Calculation of the overall risk impact score $(ORC_t^j)_i^k$ for each category using the equation

$$(ORC_t^j)_i^k = (TIC_t^j)_i^k \times (WC_t^j)_i \quad (8)$$

Y

$$(ORC_t^j)_i^l = (TIC_t^j)_i^l \times (WC_t^j)_i \quad (9)$$

I. Results

Table 5. Descriptive and predictive data of fuzzy variables

v	M	yes	v1	v2	v3	v4	v5	R2 -
v1	23.21	12.21	1,821	.654	.436	.562	.432	.37
v2	24.35	10.13		1,351	,430	.549	.385	.36
v3	25.46	15.46			1,021	.534	.436	.25
v4	20.12	13.27				1,464	.458	.16
v5	24.35	13.24					1,212	.12

v1 = New anti-plagiarism software; v2 = New Editorial Provisions, v3 = New Reference System, v4 = New Statistical Software, v5 = Dropout; M = Mean, S = Standard deviation, R^2 = Average variance extract

Table 5 shows the descriptive and predictive data of the relationships between the most used variables in the systematic review of the literature, being possible to observe positive relationships, which allowed observing the model and the meta-analytic structural equations.

Table 6. Meta-analytic structural equation model

	v1	v2	v3	v4	v5					
	UPC/SPC	*UPC/SPC*	*UPC/SPC*	*UPC/SPC*	*UPC/SPC*	*CMIN/DF*	*GFI*	*IFC*	*RMSEA*	*SRMR*
v5 ç v1	.324*		.650***		.543*	4,321	.997	.995	.007	.003
v5 ç v2		.43**	.542*	.543*	.432*	4,302	.993	.997	.008	.004
v5 v3 _		.561*	,	.432**	.328*	.4352	,990	.993	.006	.003
v5 v4 _			.430*	.218*		4,351	.993	.997	.007	.002
v5 ç v2 ç v1	.432*				.329**	4,354	.990	.995	.008	.001
v5 ç v3 ç v1		,			.543*	4,239	.995	,990	.007	.002
v5 ç v4 ç v1	.547*	.567*	.548**	.438*	.563**	4,304	.997	.990	.005	.003
v5 ç v3 ç v2				.432*	.432*	4,132	.993	.990	.004	.004
v5 ç v4 ç v2				.431*	.324*	4,325	.990	.993	.006	.001
v5 ç v4 ç v3	.329*		.432*			4,563	.991	.990	.007	.002

*v1 = new anti-plagiarism software; v2 = New Editorial Provisions, v3 = New Reference System, v4 = New Statistical Software, v5 = Dropout; df of all models is 6, UPC: unstandardized path coefficient, SPC: standardized path coefficient, GFI: goodness-of-fit index, CFI: comparative fit index, RMSEA: root mean square error of approximation, SRMR: quadratic residual standardized medium. *P<0.001*

Table 6 shows that the total effects model for the trajectory that explains desertion is due to the relationship between the appearance of anti-plagiarism software and the editorial provisions of the journals, such as the preference for single authors, with sophisticated processing techniques. Information and in a dominant language such as English.

I. Discussion

The contribution of this work to the state of the question lies in the establishment of a random effects model to explain the diffuse trajectories between risk gradients with respect to job training, considering publications from 2019 to 2022, as well as the type of literature, the knowledge creation phase and the academic division of the students, although the results are limited to the intentional sample of the consulted literature (Rosas et al., 2019). A homogeneous random effects meta-analysis of the relationship between the formation of intellectual capital and corporate reputation is recommended in order to anticipate risk scenarios.

In relation to the fuzzy logic models in which the frequencies or probability ratios of risk reduction are highlighted, the present work has proposed a meta-analytic approach of structural equations in which rival models are compared to see which one best fits the situation. Explanation of corporate reputation and the formation of intellectual capital, the main indicator of the total effects of a system. The contrast of the estimated models will allow us to notice the explanatory trajectory of the relationship between corporate reputation and academic training.

With respect to traditional meta -analyses in which the total effects of the literature consulted are analyzed to establish the influence of a source, or the proportional scale of the hegemony of various sources, the present work has proposed to observe the relationships between the variables analyzed by the literature consulted in order to establish the trajectory with the best fit and explanation of a retrospective scenario of intellectual capital formation. Future studies with the fuzzy logic scale and meta-analysis of structural equations will allow us to observe the relationship between corporate reputation and academic training.

In this sense, structural equation models are distinguished by allowing the estimation, analysis, observation and prediction of the trajectories of relationships between variables, but the present work has only included those whose logic is spread by the emergence of their effects in the academy. , vocational and job training. It is necessary to estimate the relationships between corporate reputation as a determinant of academic training and concomitant with corporate image in order to anticipate a diffuse scenario.

Future lines of research on emerging variables in the formation of intellectual capital will allow more sophisticated meta-analyses such as mixed random effects models to account for the impact of diffuse variables on the production of knowledge such as scientific articles, indicators of training quality.

I. Conclusion

The objective of this work has been to establish risk trajectories in the training process based on the selection of fuzzy variables that, due to their degree of emergence, explain desertion in the development of scientific or academic products; but the research design limits the results to the study sample, suggesting its extension to the observation of more sophisticated phenomena such as mixed random total effects and their processing in data mining, as well as the conversion of these data to the language of structures met analytics . Equation models. Corporate reputation and academic training are preponderant factors in the risk thresholds established through the fuzzy logic scale and structural equation meta- analysis.

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