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Intellectual Capital in the COVID-19 era

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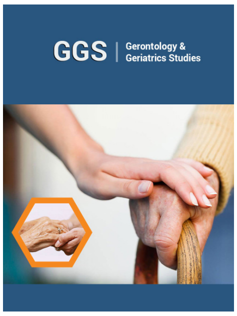

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Abstract

In social sciences, the meta-analytical fixed effects models have gained special relevance due to their predictive capacity of 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 those emerging in processes Training and research. The objective of this work was to establish fixed effects models to explain the influence of diffuse variables in the formation of intellectual capital, considering contextual, educational, academic and professional variables. A retrospective study was conducted with literature from 2019 to 2022, as well as an exploratory study with variables that have been conceptualized, but not empirically tested and correlational with an intentional selection of six studies that used diffuse variables to explain attrition. The results show that the model with the greatest adjustment is the one where the emergence of anti-plagiarism software and new editorial provisions explain the dropout, although the research design limited the results to the study scenario, suggesting its extension and sophistication with other statistical techniques.

Keywords: Capital; Intellectual; Formation; Diffuse; Model

Introduction

In the sciences of complexity, the analysis of diffuse logic has been instrumented 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 case of managers, producers and knowledge transfers [1]. The diffuse logic is due to the 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 transfer of people or goods [2]. In that tenor, the investigation; 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 [3]. Therefore, a systematic review of the educational, academic, scientific and technological systems is necessary to establish training, training and training paths for the interested parties [4].

However, traditional studies of fuzzy logic have been built based on disturbances, contingencies and disturbances in which gradients (corruption, catastrophes, collisions) are fuzzy determinants of population distribution, their capacities and resources [5]. In the case of social sciences, diffuse logic models warn of the emergence of actors such as the cases of managers, producers and disseminators of knowledge that, in interrelation with repositories and technologies, make up the metrics of the quality of processes and scientific and technological products of institutions in alliances with knowledge-creating organizations [6]. Budsankon et al. [7] they carried out a systematic review of the studies that brought effects of the environment on analytical, critical and creative thinking skills, establishing as predictors the classroom environment and intellectual abilities explain 96% of the total variance. Payborji & Haghighi [7] performed 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, the Profitability and corporate reputation. Basyith [8] he found in his review that a high percentage of Indonesian companies are family members and, consequently, such a situation would be expected to influence the profitability of companies by not having a system of intellectual capital formation, but the law of listing on the stock market when imposing hiring standards and the quality of employees, led to nepotism not influencing the recruitment of talents.

In synthesis, the formation of intellectual capital oscillates between corruption and the traditionalist nepotism until transparency in the hiring of intellectual capital, measuring its performance from the management in its academic, professional and labor training, as well as in its consolidation encrypted in the conversion of intangible assets due to the degree of impact on the value of the companies that create knowledge [9]. Precisely, it is in this phase that match the management, production and transfer of the codified knowledge in the formation of intellectual capital; professional service and work practice established by alliances between institutions and knowledge creation organizations [10]. Therefore, the objective of this work will be to establish the dissipative trajectories of the investigative training process in order to be able to observe prospectively the decision making of managers, producers and diffusers of investigative knowledge, specialized and updated as required by the indexation systems.

Material And Methods

This section presents the phase-wise description of the developed risk-impact assessment methodology [11].

Phase I: Comprehensive Populace Monitoring to determine gestion, production and transfer strategies [12]. Direct monitoring was conducted which gives a detail population count and measure of papers that are of gestion, production and transfer interest, such as types of studies, paradigm, theory, model, construct and variables (Table 1).

Table 1: Descriptive data studies.

Year	Author	Literature	Phase	Division	N
2014	Hernandez et al.,	A	D	CDS	260
2015	Morales et al.,	A	D	NSE	230
2016	Fierro et al.,	D	D	SAD	220
2017	Garcia et al.,	A	D	SSH	200
2018	Sandoval et al.,	B	P	BHS	220
2019	Carreon et al. [4],	A	M	BSI	240
2020	Espinoza et al. [11],	C	M	SSH	220
2021	Garza et al. [17],	A	P	SSH	210
2022	Meriño et al.,	B	P	SSH	200

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 on 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=Science and Arts for Design, NSE=Nature Sciences and Engineering, CDS=Communication and Design Sciences.

Phase II: Identify threats that inhibit the formation of human capital [13]. Disturbance gradients are identified based on the classification of terminal efficiency, participation in academic events such as congresses and the scientific and technological production published in repositories such as Copernicus, Dialnet, Ebsco, Latinex, Publindex, Redalyc, Scielo, Scopus, WoS and Zenodo. This helps identify threats, areas of opportunity and competitive advantages [12].

Phase III: Formation of Expert Assessment (EA) Team

El equipo incluye 10 expertos en gestión, producción y transferencia de información. Sus responsabilidades incluyen:

a) Calificación y clasificación de los cuestionarios; y

b) Dar sus valiosas opiniones para garantizar la fiabilidad de los datos.

Phase IV: Determining the Risk Impact [13]. The following are the steps to determine the impact of risk on the formation of human capital.:

Step 1: Identify t threat classes and group these into j categories to get C_t^j, where C_t^j are the threats in each category [14-17].

Step 2: Score these C_t^j to get the Threat Influence Score $S(C_t^j)_i$ ifor each t in every j and at each study site i. The scoring is done by EA Team using 5-point scale (High-5, Middle-3, and Low-1).

Step 3: Computation of Threat Influence Weights $(WC_t^j)_i$ using following sub-steps:

Step 3.1 Fuzzy pairwise comparison of each C_t^j by the EA Team using the Fuzzy Scale (Table 1).

Step 3.2: Conversion of fuzzy scale in triangular fuzzy number (TFN) $\tilde{a}_t = (a_{1t}, a_{2t}, a_{3t})$ using 9-point fuzzy scale (Table 1). The triplet (a_{1t}, a_{2t}, a_{3t}) represents the lower, middle and upper TFN for the threat t (Table 2).

Table 2: 9-point fuzzy scale.

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

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

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

Step 3.4: Compute Fuzzy Decision Weights $\tilde{F}_t$ using equation

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

Step 3.5: Computation of Decision Weights D_t for the Fuzzy Decision Weights using the equation

$$D_t = \left[\beta c_\alpha (F_{1t}) + (1-\beta) c_\alpha (F_{rt})\right], 0 \le \beta \le 1, 0 \le \alpha \le 1 \quad (3)$$

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 right value of α -cut for $\tilde{F}_t$

Step 4: Determining the Site-Risk Impact Weights $(RC_t^j)_i$ for the study sites using the equation

$$(RC_t^j)_i = (SC_t^j)_i \times (WC_t^j)_i \quad (4)$$

Step 5: Score the C_t^j according to their timing, range and severity (Table 3) in relation to how likely these 'trigger' the bird species mortality at the study site i, to get Threat Trigger Scores $(TC_t^j)_i$ (Equation (5)). The scoring is done by the EA Team members.

Table 3: Characteristics of threat.

Timing of threat	Timing score (TS)	Range of threat	Range score (RS)	Severity of threat	Severity score (SeS)
Happening now	5	Whole population/ area (>90%)	5	Quick dropout (> 30% in 1 year)	5
Likely in short term (within 4 years)	3	Most of population/ area (50-90%)	3	Moderate attrition (10-30% for 1 year)	3
Likely in long term (beyond 4 years)	1	Some of population/ area (10-50%)	1	Slow dropout (1-10% in 1 year)	1
Past (and unlikely to return) and no longer limiting	0	Few individuals/small area (<10%)	0	No imperceptible dropout (<1% in 1 year)	0

$$(TC_t^j)_i = TS + RS + SeS \quad (5)$$

Step 6: Now score the students and institutions or organizations sub-type against each C_t^j to get the Threat Influence Score for k students $(IC_t^j)_i^k$ and for l institution or organization sub-types $(IC_t^j)_i^l$. The scoring is done by experts using 5-point scale (High-5, Middle-3, and Low-1).

Step 7: Computing 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 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: Calculating the overall Risk Impact Score $(ORC_t^j)_i^k$ for each category using the equation

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

and

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

Results

Table 4 shows the descriptive and predictive data of the relationships among the variables most used in the systematic review of the literature, being possible to observe positive relationships, which allowed us to observe the model and meta-analytical structural equations (Table 5). Table 5 shows that the total effects model for the trajectory that explains the dropout is due to the relationship between the emergence of anti-plagiarism software and the editorial provisions of the journals, as would be the preference to single authors, with sophisticated processing techniques. information and in a dominant language such as English.

Table 4: Descriptive and predictive data of the diffuses variables.

V	M	S	v1	v2	v3	v4	v5	R^2
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 Referencing System, v4=New Statistical Software, v5=Desertion; M=Mean, S=Standard Deviation, R^2=Average Variance Extract.

Table 5: Model of meta-analytical structural equations.

	v1	v2	v3	v4	v5					
	UPC/SPC	UPC/SPC	UPC/SPC	UPC/SPC	UPC/SPC	CMIN/DF	GFI	CFI	RMSEA	SRMR
$v5 \leftarrow v1$	,324*		,650***		,543*	4,321	,997	,995	,007	,003
$v5 \leftarrow v2$		,43**	,542*	,543*	,432*	4,302	,993	,997	,008	,004
$v5 \leftarrow v3$		,561*	,	,432**	,328*	,4352	,990	,993	,006	,003
$v5 \leftarrow v4$			,430*	,218*		4,351	0.993	,997	,007	,002
$v5 \leftarrow v2 \leftarrow v1$	,432*				,329**	4,354	0.99	,995	,008	,001
$v5 \leftarrow v3 \leftarrow v1$		,			,543*	4,239	0.995	,990	,007	,002
$v5 \leftarrow v4 \leftarrow v1$	,547*	,567*	,548**	,438*	,563**	4,304	0.997	0.99	,005	,003
$v5 \leftarrow v3 \leftarrow v2$				,432*	,432*	4,132	0.993	0.99	,004	,004
$v5 \leftarrow v4 \leftarrow v2$				,431*	,324*	4,325	0.99	0.993	,006	,001
$v5 \leftarrow v4 \leftarrow v3$	,329*		,432*			4,563	0.991	0.99	,007	,002

v1=New anti-plagiarism software; v2=New Editorial Provisions, v3=New Referencing System, v4=New Statistical Software, v5=Desertion; 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: Standardized Root Mean Square Residual. *$P<0.001$

Discussion

The contribution of this work to the state of the matter 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 2014 to 2019, 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 literature consulted. In relation to the fuzzy logic models in which the frequencies or probability proportions of risk reduction are highlighted, the present work has proposed a meta-analytical approach to structural equations in which rival models are compared in order to observe the one that best fits the prediction of attrition, the main indicator of the total effects of an intellectual capital training system.

With respect to the traditional meta-analyzes in which the total effects of the literature consulted to establish the influence of a source are analyzed, or the proportional scale of the hegemony of diverse 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 better adjustment and explanation of a retrospective scenario of intellectual capital formation. In this sense, the models of structural equations 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 diffused by the emergence of its effects on academic, professional and labor training. Future lines of research concerning the emerging variables in the formation of intellectual capital will allow more sophisticated meta-analyzes 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 formative quality

Conclusion

The objective of this work has been to establish the risk trajectories in the training process based on the selection of diffuse variables that, due to their degree of emergency, explain the defection in the elaboration of scientific or academic products; but the research design limits the results to the study sample, suggesting its extension for 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 language of meta-analytical structural equation models.

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