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An Application of TOPSIS Approach in Determination of Spread Influencers in a Competitive Industrial Space: Evidence from the Banking Network of Ghana

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Abstract

In this paper, we investigated into aggregated social influence. We adopted and modified the weighted TOPSIS approach to ascertain the overall social influences of management members in the banking network of Ghana. The weighted TOPSIS method employs a composite approach of classical centrality influence that uses the position of the actor in the network hierarchy, the intensity of his interaction, extent of his connectivity and flow of information within the network. The approach offers an extensive advantage in ensuring holistic decision making by implementing an algorithm that employs a multi-criteria approach. The study revealed that although most single attributes were significant in measuring the niched aspect of social influence, the closeness to ideal that was attained through a weighted TOPSIS algorithm showed stronger ties and was conclusive enough to judge the social influence of actors to warrant its sole application in the determination of spreaders or influential nodes in a network. To enhance efficiency in decision making in relation to employment and layoffs, it is recommended that a social network analysis which adapts a multi-attribute decision-making approach that reflects both individual strength and weaknesses in totality for all aspect of social influences should be employed. We recommend further studies into Actor Ranking and its impact on recruitment practices for organizational innovation.

Keywords

Social Network Analysis, TOPSIS, Banking Network, Human Capital, Centrality Measures

1. Introduction

Efficiencies in organizational operations in competitive markets are of key interest to all organizations in recent times. Subsequently, organizations make decisions in the areas of employment and downsizing through layoffs in an attempt to remain viable in competitive markets [1]. Employment and downsizing can reduce the cost of doing business but may yield less than desired results if not properly executed. The intent of human resource managers and recruiters in employing or downsizing is to enhance their strategic positions by reducing the cost of doing business while retaining core competencies and desired skill sets of the surviving members of the organization.

Clandestinely, the sustainable growth of an organization is dependent on the ability of the current employees that possess the required human capital to pass it on to new and old employees alike that do not possess this required human capital. Thus, diffusion of this specialized knowledge, skills, ideas, and experiences is per scientific principles from a higher concentration area to a lower concentration area [2] [3] [4].

Human Resource Managers and Recruiters in general are therefore in more recent times challenged with the responsibility to improve if not optimizing their recruiting practices and succession planning for competitive advantage. In today's increasingly knowledge-based economy, effective recruitment is likely to be the most critical human resource function for organizational success and survival [5]. Carol [6] adds that recruitment strategies in human resource management both internally and externally are focused on strengthening competitive advantage by assembling the best and most influential human capital in achieving organizational goals and remaining competitive enough in maintaining or increasing market shares. Mostly, recruiters target influential nodes or spreaders in the quest to gain a competitive advantage in their market space. It is important to establish that the possession on a high human capital alone is not enough to ensure the transfer of these skills, knowledge, ideas, and experiences but also the role and relevance of the actor in terms of the transfer of human capital.

The challenging economic conditions push organizations to resort to downsizing which alters operations to remain competitive. Globally, organizations in almost every industry use downsizing to maximize efficiencies, reduce operating costs and increase profits as part of strategic planning. Surviving employees are integral to organizational success. If management of downsizing organizations is to achieve desired results of layoffs, surviving employees' skill set and organizational commitment must remain intact [7]; otherwise, employees whom organizations' rely on driving revitalization may not possess the required human capital partly because layoffs can negatively affect influencers or pillars of the organizational success. Any loss of talent may minimize the expected benefits of layoffs.

Employees are social beings who tie and break social links over time and space. Social links may be in the form of family, friends, colleagues, teachers, among others. Through this links and interactions, employees influence and change the ideas, skills, knowledge, experiences, etc of each other. A colleague at work sharing his or her experience on the usage of new technology and how to overcome the challenges associated with the user may influence others acceptance or rejection of this technology. Further, sharing ideas on a new project under implementation in one's organization in a professional association group impacts on its adaptation and implementation in other organizations in the future. Aşcı, Tan [8] viewed the concept of social learning as the effective way of ensuring the sustainability of a society's growth that occurs through social interactions and processes between actors within a social network, either through direct or indirect interaction. The efficacy of the social learning theory has been well established in recent studies provoking the interest of researchers in the application of social network theories in business studies. Employees influence, inspire and learn from each other and its resultant, latent cooperation that can be observed in social networks, where interacting users are connected with each other. Studies have established that nodes do not have the same importance in a network and therefore it is important to rank nodes. In the field of human resource management, the removal or addition of an employee (hiring, retirement, transfer, resignation or dismissal) can cause the collapse or malfunction of the network. Thus, some employees control the stability and competitive advantage that an organization enjoys in a competitive industrial space. The scarcity and competitiveness of the labour market swing organizations to make attempts to determine a set of employees who can diffuse [9] knowledge, skills, ideas that offer a competitive advantage through social networks. Consequently, the number of people one can influence or be influenced by to adopt or learn a new knowledge coupled with the quality of knowledge possessed by the influencer is important for competitive advantage.

This study investigated into aggregate social importance of a node premising from an optimal point of view of each node in their importance in the various centrality measures thereby identifying the most important spreaders in a competitive network space. It will employ a multi-attribute decision making model in this respect. Again, the study will assess the correlation between the TOPSIS determined importance (closeness to aggregated ideal) and other single attributes determined importance and finally, we will apply the TOPSIS weighted importance to the banking network of management in the Ghanaian developing economy.

2. Literature Review and Theories

2.1. Centrality Measures

Many researchers have keenly researched into the social interactions basically on the characteristics of actors or nodes and the edges or ties strength. The two characteristics are manipulated through various approaches in ranking or identifying influential nodes to help the spread of knowledge, skills, and ideas. Different approaches have been put forward in the determination of important nodes. The most classical approach is the centrality measures [10]. Each centrality measure proposed or adopted to investigate the importance of nodes in a social network is done from a particular point of view [11] [12]. **Degree centrality**, for instance, assesses the importance of nodes base on the quantitative connectivity, even within the degree in a directed network, there are indegree centrality and outdegree centrality where importance is measured based on quantification of in and out connectivity [10]. Chuluun, Prevost [13]. Landherr, Friedl [14] in a critical review of centrality measures explained that **Closeness centrality** measures the average length of the shortest path between the node and all other nodes in the graph. Accordingly, the more central a node is, the closer it is to all other nodes in the network. Another centrality measure is **Betweenness centrality** which quantifies the number of times a node acts as a bridge along the shortest paths between two other nodes. Bonacich [15] explained **Eigenvector centrality** as a measure of the influence of a node in a network by assigning relative scores to all nodes in the network based on the assumption that connection to high-scoring nodes contributes more to the node in question than equal connections to low-scoring nodes. Additionally, **Information centrality** assesses how central a node is in terms of information spread within a network. These and many other centralities are targeted at a specific dimension of importance in a network.

2.2. Human Capital Transfer

Organizations through various approaches transfer their knowledge both explicit and tacit to their employees to niche their portion in the competitive industrial space. This transfer process comes in forms such as inter-organizational, inter-unit or groups in the same organization, or within members or actors in an organization [5] [16] [17]. The conditions of transfers are hinged on diffusion and communication processes. Firstly, highly concentrated employees attempt to organize, create, capture or spread knowledge, skills, ideas, and experiences (human capital) to other employees who do not possess or possess but inadequate to meet sustainability levels for future usage. Secondly, human capital transfer process usually is very similar to a communication process that occurs between two entities just as in the case of diffusion [18]. Dass and Chelliah [18] opine that Human Capital transfer is of major concern to all organizations because of its time-bound relevance. Organizations, therefore, employ both the "make" and "buy" succession planning strategies to remain relevant and competitive in the industrial space. Thus, the timing of the transfer of human capital to keep employees and the organization innovative, productive and competitive is as important as the human capital hub [19]. This has informed human resource policies and practices.

2.3. Multi Attribute Decision Making and Topsis

Humans as social beings are always faced with choices to be made from a number of options. Multi-attribute decision making (MADM) deals with situations in which a decision maker has to make a choice out of a set of choices, based on information about these choices on a number of attributes. Multi-attribute decision making gives decision makers' the opportunity to maximize the process of decision making in such a way that all relevant and available information is used and integrated in order to arrive at a preference order of the choices [20] [21].

One approach rationally adopted in multi-attribute decision making options is the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [22] [23] [24]. TOPSIS method minimizes the distance to the ideal solution while the distance to the lowest point is maximized and uses a compensatory accumulation method that evaluates several choices by considering the weighted criteria. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is extremely beneficial when a decision-making process is complex. The reason is that TOPSIS can prioritize multiple-choice criteria into a hierarchy by assessing the relative importance of criteria and can thus generate an overall ranking of the alternatives.

TOPSIS has been applied in so many studies in different disciplines. Business studies [23] [25] [26] [27] [28], Ecological studies [29] [30], Aviation studies [31], Mathematical sciences [32] and Engineering [33] [34].

3. Methodology

For the purpose of this study, 6 commercial banks listed on the Ghana Stock Exchange (GSE) will be employed. Only Banks listed and operating in Ghana were considered, **Table 1** shows the listed banks operating in Ghana from which data was collected. The Banks were Access Bank, Agricultural Development Bank, EcoBank, GCB Bank Limited, Republic Bank formerly HFC Bank Ghana Limited, and Standard Chartered Bank Ghana Limited. The aggregated management strength of all six Banks was 64. Data were extrapolated from the curriculum vitae of actors, as well as industrial reports. The UCINET 6 for Windows version 6.658 and Excel was used as the analytical tool for the network.

Table 1. Listed Banks and Management team size

No.	Banks in 2019	Management team size
1	Access Bank	11
2	ADB Bank Limited	13
3	Ecobank Ghana Limited	7
4	GCB Bank Limited	13
5	Republic Bank (HFC Bank Ghana Limited)	9
6	Standard Chartered Bank Ghana Limited	11
	Total	**64**

Source: (Wikipedia, 2019) and field data 2019

Table 2 represents the variables weight determination for the network. The aggregated value of an individual based on the variables of assessment as determined in Table 2 is $Z_v = \sum_v^n (S + B + E + A + P)$ where

Table 2. variable weight determination.

Variables	Descriptions
1) Academic qualification	It was detected from the data that the minimum academic qualification was a bachelor degree and the highest was a PhD; This was expressed as $A = \sum_{i=1,2,3} a_i$ where a = Corresponding academic qualification score A = Total Score obtained on individual academic qualifications i = Individual scores of academic equation
2) Educational Institutions attended	The Times Higher Education Ranking was used. This is expressed as; $S = S_{ij} = \sum_{i=1}^n \sum_{j=1}^n U_{ij}$ Decomposing (1), gives: $\sum_{y=1}^n S_{ji} = \sum_{i=1} U_i$ where (1) and (2) are conditionally premised on $\left.\begin{matrix} S_{i1} = U_{i1} + U_{i2} + \cdots + U_{in} \\ \vdots \\ S_{Ni} = U_{N1} + U_{N2} + \cdots + U_{Nn} \end{matrix}\right\}$ premise 1 $\left.\begin{matrix} S_{j1} = U_{j1} + U_{j2} + \cdots + U_{jn} \\ \vdots \\ S_{Nj} = U_{N1} + U_{N2} + \cdots + U_{Nn} \end{matrix}\right\}$ premise where S_{i1} = Total universities an individual has attended. U_{in} = Individual score of a University i & j = Universities
3) Countries	The 2017 Global Human Capital Index was adopted. This was expressed as $B = B_{ij} = \sum_{i=1}^n \sum_{j=1}^n X_{ij}$ Decomposing (1), gives: $\sum_{y=1}^n B_{ji} = \sum_{i=1} X_i$ where (3) and (4) are conditionally premised on $\left.\begin{matrix} B_{i1} = X_{i1} + X_{i2} + \cdots + X_{in} \\ \vdots \\ B_{Ni} = X_{N1} + X_{N2} + \cdots + X_{Nn} \end{matrix}\right\}$ premise 1 $\left.\begin{matrix} B_{j1} = X_{j1} + X_{j2} + \cdots + X_{jn} \\ \vdots \\ B_{Nj} = X_{N1} + X_{N2} + \cdots + X_{Nn} \end{matrix}\right\}$ premise 2 where B_{i1} = Total countries an individual has visited X_{in} = Individual score of a country i & j = Countries
4) Experience	The work experience attributed coefficient of an actor within this study was derived as $E = E(x) = n$ where E = Total score of Experience n = Number of years of experience

Continued

5) Professional Association	A point was allocated per association such that the total number of professional association points scored was commiserative of the total number of associations an actor listed membership of on his or her cv. This is aptly represented as $P=\sum_{i=1}\sigma_i$ where: P = Total score for professional association σ = Professional qualifications i = Individual scores of professions

Z = The individual employee' cumulative HC;

S = Post-secondary educational institutions;

B = Countries;

E = Experience;

A = Academic qualification;

P = Professional association.

The weight of the actors was infused in the development of the network. The condition for interaction between actors in a network has always been contingent on proximity (closeness, distance) and accessibility (centrality) and similarities (clusters). The argument is that all things being equal, proximity, accessibility, and similarities are catalysts for establishing relationships between actors within a network. The network was undirected in nature as sharing of knowledge in an organization takes both formal and informal thereby given little credence to the direction.

Our Approach

We approached our study following the outlined steps in **Figure 1**.

Actors within a complex network in a competitive industrial space do not have the same influence on the systems. Competitive advantage is affected by the ability of actors to influence phenomena or other actors within the network spaces. Researchers have combined ordinary differential approaches to explain how network metrics can be used to explain the interactive strength of actors within complex networks. The metrics of the network analysis, then serve as the basis for understanding the impact, role and relevance of actors within complex spaces [13] [14] [34] [35] [36] [37] [38].

A weighted TOPSIS approach will be employed to ascertain the actor's influence and proportional control of human capital in the banking network. The data to be obtained from the banking network $E_{i,j}$ and with the connection contingencies made up of centrality matrix $M=(E_{mn})$ such that M is composed of all the diffusion and adoption parameters that i and j depend on to build dyadic relations. Normalizing this will allow M to be written as

$$M=r_{ij}=\frac{E_{mn}}{\sqrt{\sum_i^m E_{ij}^2}}, i=1,\cdots m; j=1\cdots,n \qquad \text{Equation (1)}$$

Thus, by multiplying the columns of the obtained normalized matrix by the determined weight of the interaction between actors i and j, a new decision matrix $K = (k_{mn})$ is obtained such that a new network $F_{i,j}$ is developed with a weighted w matrix

$$F = h_{ij} = w_j \times r_{ij}, i = 1, \cdots, m'j = 1, \cdots, n \qquad \text{Equation (2)}$$

But $w_j = \frac{1}{n}$ and the weight of j actors remain same.

Further, to deduce our positive and negative ideal influencers within the banking network, the study will denote the positive ideal as A^+ and the negative ideal as A^-. Referencing the approach by Liao, Mariani [39].

$$A^+ = \{h_1^+, h_2^+, \cdots h_n^+\} = \{(\max_i P / j \in K_b)(\max_i P / j \in K_c)\} \qquad \text{Equation (3)}$$

$$A^- = \{h_1^-, h_2^-, \cdots h_n^-\} = \{(\max_i P / j \in K_b)(\max_i P / j \in K_c)\} \qquad \text{Equation (4)}$$

Thus, by considering the separation condition of S, such that S_i^+ is reminiscent of actor $i's$ decision that is closer to A^+ while S_i^- reflects close proximity to A^- allow us to measure actor importance in the banking network as reflected by their relative closeness to ideal human capital diffusion and adoption and is reflected in

$$S_i^+ = \sqrt{\sum_{j=1}^n (h_j^+ - h_{ij})^2}, i = 1, \cdots m; j = 1, \cdots, n \qquad \text{Equation (5)}$$

$$S_i^- = \sqrt{\sum_{j=1}^n (h_j^- - h_{ij})^2}, i = 1, \cdots m; j = 1, \cdots, n \qquad \text{Equation (6)}$$

Finally, the relative closeness to the idea solution S as a means of determining influential diffusers can be derived from Equation (5) and Equation (6) as

$$Q_i = \frac{S_i^-}{S_i^- + S_i^+}, i = 1, \cdots, m \qquad \text{Equation (8)}$$

The final output from Equation (8) will then be ranked and used as the optimal influence of industry and actors in the network.

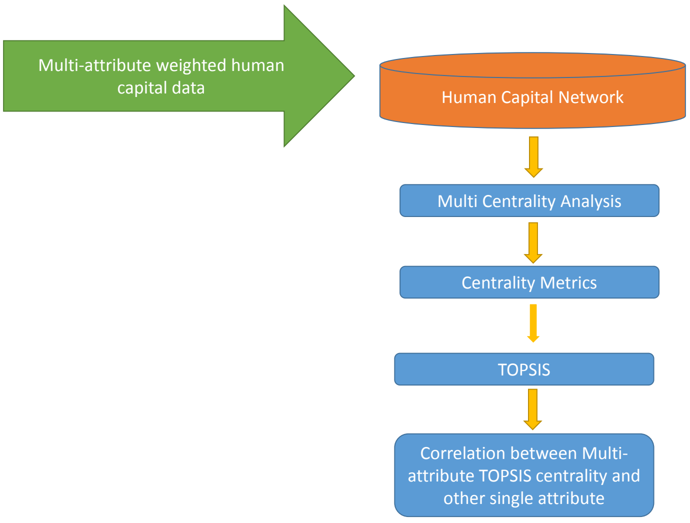

Figure 1. Study outline.

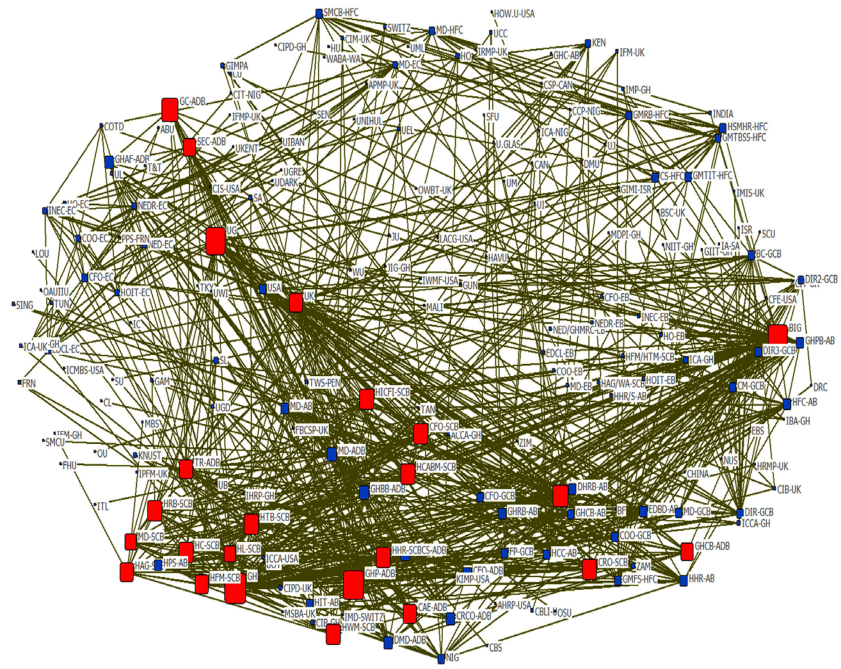

Figure 2. Weighted TOPSIS financial network.

Figure 2 represents the network of the banking industries based on the weighted attributes from the TOPSIS run algorithms.

4. Results

Table 3 represents the centrality measures and actor ranking of importance in each measure. From a glance, there is a significant difference between actors and their importance in the different individual importance measures. From Table 3, CRO-SCB ranked first in Degree Centrality, 17^{th} in Closeness Centrality and second (2^{nd}) in Closeness to Ideal Centrality. Further HO-EC who ranked least, 64^{th}, in the Closeness to Ideal Centrality the rank improved to 47^{th} position. Still in Table 3, MD-SCB ranked 39^{th} position in terms of Betweenness Centrality, 25^{th} in Closeness Centrality but ranked first in the Closeness to Ideal Centrality that takes into consideration the totality of centralities in relation to the ideal situation ranking. The DIR-GCB ranked 22^{nd} in both Eigenvector Centrality and Information Centrality, First (1^{st}) in Closeness and Betweeness Centralities but ranked 4^{th} in the Closeness to Ideal Centrality.

In summary from Table 3, a microscopic view establishes the significance of an aggregated social influence as actors took different ranks in different measures. For instance, the Managing Director of SCB (MD-SCB) was ranked as the most influential (1^{st}) in the closeness to the ideal that is the aggregation of all the other measures considering the strength and weaknesses of actors in optimizing their rank but 39^{th} out of 64 actors in the banking network. This finding strongly aligns with Muruganantham and Gandhi [40] which suggests that a multi-attribute TOPSIS rated decision making employs efficiencies that reduces errors of judgement.

Table 3. Centrality measures and rankings.

Actor	DC	DCRank	EVC	EVCRank	CC	CCRank	BC	BCRank	IC	ICRank	CI	CIRank
BC-GCB	0.059	10	0.056	26	0.436	2	5	3	2.68	15	0.43	18
CAE-ADB	0.031	44	0.042	38	0.421	37	0.353	55	2.56	41	0.29	48
CFO-ADB	0.031	44	0.037	47	0.421	37	1.258	37	2.535	46	0.28	52
CFO-EC	0.039	34	0.049	32	0.394	56	1.444	34	2.595	32	0.41	22
CFO-GCB	0.028	50	0.037	47	0.43	8	0.577	50	2.528	48	0.29	51
CFO-SCB	0.05	20	0.189	9	0.424	27	0.663	46	2.683	14	0.37	36
CIO-SCB	0.094	3	0.27	3	0.43	8	2.058	23	2.774	2	0.49	3
CM-GCB	0.023	56	0.029	55	0.428	18	0.284	57	2.452	56	0.20	61
COO-EC	0.041	31	0.038	45	0.394	56	2.308	17	2.567	40	0.43	16
COO-GCB	0.034	41	0.044	34	0.43	8	1.246	38	2.569	38	0.38	31
CRCO-ADB	0.053	18	0.055	27	0.423	32	2.626	15	2.658	20	0.42	21
CRO-SCB	0.105	1	0.303	2	0.429	17	3.434	10	2.773	3	0.53	2
CS-HFC	0.021	61	0.027	59	0.412	51	0.603	49	2.411	60	0.30	46
DHRB-AB	0.041	31	0.057	24	0.43	8	2.154	19	2.621	29	0.37	35
DIR2-GCB	0.051	19	0.07	17	0.432	4	4.932	4	2.717	5	0.44	9
DIR3-GCB	0.047	24	0.05	30	0.432	4	2.796	13	2.617	30	0.43	17
DIR-GCB	0.087	4	0.059	22	0.44	1	9.656	1	2.652	22	0.49	4
DMD-ADB	0.059	10	0.062	21	0.423	32	2.33	16	2.687	13	0.44	8
EDBD-AB	0.055	14	0.066	20	0.43	8	3.399	11	2.671	18	0.44	11
EDCL-EC	0.028	50	0.03	53	0.392	62	0.611	48	2.488	52	0.30	43
FP-GCB	0.028	50	0.035	51	0.43	8	3.06	12	2.48	53	0.30	45
GC-ADB	0.025	55	0.029	55	0.419	41	0.231	59	2.473	55	0.20	62
GHAF-ADB	0.03	48	0.033	52	0.419	41	0.17	61	2.528	48	0.18	63
GHBB-ADB	0.055	14	0.067	18	0.424	27	1.004	42	2.69	11	0.40	25
GHCB-AB	0.048	21	0.057	24	0.43	8	0	63	2.657	21	0.41	23
GHCB-ADB	0.023	56	0.027	59	0.419	41	1.963	25	2.442	58	0.18	64
GHCS-ADB	0.031	44	0.041	41	0.421	37	1.345	36	2.544	43	0.29	49
GHP-ADB	0.032	43	0.036	50	0.421	37	0.844	44	2.552	42	0.28	54
GHPB-AB	0.048	21	0.058	23	0.432	4	4.571	5	2.639	26	0.37	34
GHRB-AB	0.042	29	0.052	29	0.43	8	1.418	35	2.635	27	0.37	33
GMFS-HFC	0.039	34	0.044	34	0.417	46	3.646	9	2.576	36	0.37	32
GMRB-HFC	0.021	61	0.02	63	0.412	51	1.02	41	2.388	61	0.31	42
GMTBSS-HFC	0.022	59	0.022	62	0.412	51	2.235	18	2.375	62	0.32	40
GMTIT-HFC	0.026	54	0.039	43	0.412	51	1.17	40	2.477	54	0.36	37
HAG-SCB	0.054	16	0.188	10	0.414	47	1.621	31	2.677	16	0.39	29
HCABM-SCB	0.044	26	0.198	7	0.424	27	1.748	26	2.691	10	0.27	59
HCC-AB	0.039	34	0.17	14	0.43	8	4.092	8	2.643	24	0.34	38

Continued

HC-SCB	0.054	16	0.046	33	0.425	25	0.52	52	2.577	35	0.39	27
HFC-AB	0.031	44	0.044	34	0.428	18	2.094	21	2.541	44	0.28	53
HFM-SCB	0.062	7	0.21	6	0.414	47	0.768	45	2.712	7	0.44	14
HHR-AB	0.056	13	0.071	16	0.419	41	1.655	29	2.69	11	0.45	7
HHR-SCB	0.043	27	0.173	12	0.423	32	0.256	58	2.643	24	0.28	56
HICFI-SCB	0.048	21	0.183	11	0.424	27	0.487	53	2.674	17	0.34	39
HIT-AB	0.03	48	0.039	43	0.427	20	2.078	22	2.523	50	0.29	50
HL-SCB	0.068	6	0.221	4	0.427	20	1.611	32	2.736	4	0.43	15
HO-EC	0.02	64	0.015	64	0.293	64	0	63	2.355	64	0.29	47
HOIT-EC	0.037	38	0.04	42	0.392	62	0.289	56	2.576	36	0.44	10
HPS-AB	0.028	50	0.042	38	0.426	22	0.091	62	2.529	47	0.27	58
HRB-SCB	0.062	7	0.214	5	0.426	22	1.623	30	2.713	6	0.42	20
HSMHR-HFC	0.021	61	0.028	58	0.412	51	2.056	24	2.371	63	0.31	41
HTB-SCB	0.058	12	0.193	8	0.426	22	1.73	27	2.706	8	0.40	26
HWM-SCB	0.043	27	0.172	13	0.423	32	0.432	54	2.644	23	0.28	57
INEC-EC	0.047	24	0.05	30	0.394	56	0.848	43	2.628	28	0.46	6
MD-AB	0.071	5	0.073	15	0.433	3	5.57	2	2.702	9	0.46	5
MD-ADB	0.061	9	0.067	18	0.424	27	4.417	6	2.671	18	0.44	11
MD-EC	0.041	31	0.044	34	0.394	56	1.721	28	2.589	33	0.41	24
MD-GCB	0.039	34	0.054	28	0.431	7	1.482	33	2.617	30	0.39	28
MD-HFC	0.037	38	0.038	45	0.413	49	2.124	20	2.54	45	0.43	19
MD-SCB	0.101	2	0.334	1	0.425	25	1.21	39	2.783	1	0.57	1
NED-EC	0.042	29	0.037	47	0.394	56	2.657	14	2.586	34	0.44	13
NEDR-EC	0.036	40	0.03	53	0.394	56	4.148	7	2.502	51	0.38	30
SEC-ADB	0.022	59	0.027	59	0.419	41	0.231	59	2.426	59	0.21	60
SMCB-HFC	0.023	56	0.029	55	0.413	49	0.544	51	2.446	57	0.30	44
TR-ADB	0.033	42	0.042	38	0.422	36	0.648	47	2.569	38	0.28	55

Degree Centrality (DC), Eigenvector Centrality (EVC), Closeness Centrality (CC), Betweenness Centrality (CB), Information Centrality (IC), Closeness to ideal (CI).

Table 4 shows correlational studies of the raw scores from the field to the various centrality measures. From Table 4, the correlation of the various centrality with the field data is assessed. Closeness centrality and Betweeness centrality was not significant with correlation of 0.14 and 0.44 respectively. Closeness to Ideal Centrality, Information Centrality, Eigenvector Centrality and Degree Centrality were significantly correlational with the field data of the managers. Ranking the correlational strength from the least to most significant, the centrality measures of Eigenvector was the least with 0.53, followed by Information centrality with 0.75, Degree Centrality with 0.88 and Closeness to ideal centrality showing the most correlational with the data.

Table 4. Correlation of centrality measures and field data.

CI	IC	BC	CC	EVC	DC
0.98	0.75	0.44	0.14	0.53	0.88

Degree Centrality (DC), Eigenvector Centrality (EVC), Closeness Centrality (CC), Betweenness Centrality (CB), Information Centrality (IC), Closeness to ideal (CI).

In summary from Table 4, although most of the measures had a strong correlation with the field data, the closeness to ideal measure had a stronger correlation. From the results, it is justifiable to use the Closeness to Ideal centrality ranking in social network analysis as suggested by Chou, Yen [27] because it does not only correlate but shows a stronger correlation to the field data as compared to any of the single attribute decision making measures. It therefore accounts for the diversity of strength in actors in decision making.

5. Conclusions

Previous studies on ranking influential actors within networks have predominantly focused on individual centrality measures such as Degree centrality, Closeness Centrality, Information Centrality, Betweeness Centrality and Eigenvector Centrality [41], which overlook a unifying ground for the different purpose driven centrality measures. In the view of Rossi, Blake [38] decision making with single attributes turns to side-line of the importance of other equally significant measures in determining worker relevance. The emergence of different measures of influence in social network analysis is the conviction of the unreliableness of the individual measures of centrality in reaching universal reliability as suggested by Deng, Yeh [25] [42]. It was therefore, important to look at a broader and an all-inclusive methodology of ranking spreaders in social networks.

The results in this study revealed that, although most single attributes were significant in measuring the niched aspect of social influence, the closeness to ideal that was attained through a weighted TOPSIS algorithm showed stronger ties and was conclusive enough to judge the social influence of actors to warrant its sole application in the determination of spreaders or influential nodes in a network. Again, the comparative analysis of the various individual ranking indicated that the importance of actors was different depending on the focus of centrality. Thus, a more influential actor in the same network in terms of Degree Centrality that focuses on the quantitative measure of actors connections turned to have a low influence in the Information centrality that focuses on the importance of an actor in the spread of information in a network. This was encouraging as it aligned itself logically to many other researchers [12] [41] who propose an amalgamation of the individually niched centralities into a socially acceptable aggregated influence of actors on networks. Our approach therefore, offered an extensive advantage in ensuring holistic decision making by implementing an algorithm that employs a multi-criteria approach, bringing all the centralities meaningfully under one umbrella.

Applying our findings to decision making in the field of human resource management, hammering on the concept of efficiency in relation to employment and layoffs of labour, it is recommended that a social network analysis which adapts a multi-attribute decision-making approach that reflects both individual strength and weaknesses in totality for all aspect of social influences should be employed. This is justifiable from the results of our study that pitches the Closeness to Ideal Centrality as the most efficient among the assessed centralities in decision making. We recommend further studies addressing the relation between influential nodes and their impact on organizational innovation.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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