The Role of Individual Actors and Banks in Human Capital Development: Evidence from the Banking Network of Ghana

Author’s Details:
(1) Alex Boadi Dankyi * (2) Kong Yusheng (3) Dr. Dankyi Aframea Lydia (4) Dankyi Kwakyewaa Joyce (5) Olivier Joseph Abban (6) Antoinette Asabea Addo

Jiangsu University, School Of Economics And Finance - China
University Of Cape Coast, College Of Distance Education
Jiangsu University, School Of Economics And Finance - China
Jiangsu University, School Of Public Administration - China
Corresponding Email: Alexboadidankyi@Stmail.Ujs.Edu.Cn

Abstract
The variability of the possession of the needed human capital and the ability of actors to transfer knowledge in institutional networks is of major concern in modern times for competitiveness and institutional performance. The study assessed the role of individual actors and banks in human capital development. The study adopted network analysis and Ordinary Least Square regression (OLS) to ascertain the magnitude and direction of the effect of the explanatory variables and dependent variables. The study measured the efficiency of the human capital network and assessed the key attributes of the network to efficiency. From the results, the study established that the network was 59.8% efficient in human capital development. The study, however, revealed that there was an inverse relationship between efficiency and density. The variables in regards to the model specified to indicate that each variable has a statistically significant impact on the dependent variable for each bank however Closeness to the Ideal (CI) showed a stronger significance comparatively. The following recommendations are made in light of the findings and conclusion; Banks should engage in networking activities to enhance their human capital, however, greater attention should be paid to the egonet where efficiency in human capital development will increase relatively better; that human resource managers in their employment take into consideration the fitness role of the employee within the ego net in terms of their centrality roles in human capital development. However, in the situation of cost-effectiveness, the closeness to ideal optimization centrality should be adopted. Finally, a constant and renewable source of information through activities of research and development, professional networking participation, both on the job and off the job training activities should be factored in policies of institutions to enhance human capital development at organizational levels.

Keywords: Centrality measures; Human capital Development; Network Efficiency; Closeness to Ideal; TOPSIS.

1.0 Introduction

The recent acceptance of networks and its evolution and application in numerous studies cutting across different disciplines like computer sciences, biological sciences, economics, and business studies is the result of the identification of the complexities that exist in human interactions. Network studies extrapolate the dynamics and complexities of interactions not only taking into consideration the characteristics of the links or ties but also the actors or edges, (Frei et al., 2020; Raman & Grover, 2020). The actor attributes and its impact has gained recognition in identifying the dynamics and complexities of network studies, (Chahin, Hoffmeister, Paetzold, & Salehi, 2017). 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 (Borgatti, 2005; Borgatti & Halgin, 2011; Chuluun, Prevost, & Upadhyay, 2017; Ilyas & Radha, 2011; Landherr, Friedl, & Heidemann, 2010; Rossi, Blake, Timmermann, Tonks, & Wermers, 2018)

Human capital development from the social learning perspective uniquely considers the impact of professional interactions as well as colleague workers influences on the acquisition and diffusion of knowledge, skillset, ideas, and perspectives with the aim of transforming initial set of human capital,
(Lehmann-Willenbrock & Allen, 2018; Rosales, 2015; Sun, Li, & Ghosal, 2020). Deductively, the characteristics of the actors in the network are very important in accessing the growth of the network in terms of human capital transformation and subsequently performance.

1.1 Contribution to the study

In this study, two key questions will be addressed. First to assess the efficiency of the network and its relation to density, betweenness and information flow. Secondly the micro-level attributes of degree centrality, eigenvector centrality, betweenness centrality, information centrality and optimized centrality of closeness to ideal on human capital development.

2.0 Literature Review

2.1 Human Capital

The human capital theory is associated with the neoclassical school of thought in economics. It therefore fundamentally considers individuals as rational humans who seek to maximize their own economic interest. Human capital theory can be traced back to the theory of macroeconomic development The acknowledged and much-researched factors of production in the 1950s included land, labor, and physical capital, (Becker, 2002). However, by the 1960s, economists had great difficulty in explaining the growth of the American economy based on the above factors of production. The empirical works of Becker, Schultz, and Mincer seem to have gained the grounds within that time challenging the existing growth model and proposing human capital as the explanative element in the unexplainable growth pattern of the American economy. Human capital, therefore, constitutes the collection of human endowed resources such as knowledge, skills, talents, abilities, experience, training, judgment and wisdom possessed individually and collectively by individuals in a defined population set that has an economic value. Bechtel (2007) in agreement opines that one's worth to an economic entity (Nation, state, firms, and industries) is measured by the degree of possession of human capital needed to accomplish their transactions. The basic premises of the theory, therefore, takes into account the aggregated stock of competencies, knowledge, social and personal attributes embodied in the ability to create intrinsic and measurable economic value. As Weatherly (2003) puts it "development is primarily through the application of knowledge, skills and analytical methods in economic task.

The works of Becker and his perspective still play a major role in growth models by supporting that the employees' knowledge and skills can develop through investment in education and training, (Schwabe & Nyga-Lukszewska, 2017). Disputing the earlier works that posited companies had little incentive to invest in the skills of their workers because trained workers could quit working for other employers who could use those skills, Becker believed that, in general, investment in education and training would increase productivity; however, it is the type of training that determines who will pay for the training; the employee or the employers. He further theorized that organizations should be more willing to share the training costs of unique and competitive driven human capital because this is of great value to the existing companies. Thus it is observational factual that potential employers do not benefit from the same productivity gains if employees change jobs because the mission and needs of organizations may differ. The only time the company will be less willing to pay is when training for general skills.

Despite the flamboyant and simplified nature of human capital theory birthed by Becker, there are a number of practical and theoretical criticism with his theory over the years. First, Kwon (2009) pointed out that Becker's initial research focused on education and income whiles ignoring the role of worker experience. They emphasized that Becker's refusal to measure experience, even though it is important to employers because employers value it in the processes of recruitment, selection, and employment. Further, they argued that Becker's initial works ignore any investment in education or training that is not formal and requires financial support. Thus too much emphasis is placed on formal education and investment in training (i.e., general and specific training) and ignores the role of informal learning and training. Informal learning is essentially action-oriented learning which employs learning by doing, or by learning from experience. For example, employees can learn a lot of accidental attempts of varying processes and methodologies at work.
within routine works. Jia (2020) supports this when they emphasize that informal learning is particularly prevalent in the employment of workers in the early stages of learning.

Finally, Becker’s theory largely ignores the role of non-cognitive abilities. Non-cognitive skills and abilities have been increasingly valued in recent years (Bedford, Bisbe, & Sweeney, 2019; Maciel & Camargo, 2016). In contrast to cognitive skills, non-cognitive skills are not directly related to reasoning in the process of acquiring knowledge through the senses, experience, or other means. Non-cognitive skills including behavior, mentality, attitudes, learning strategies and social skills have a profound impact on human learning. For example, an employee may have strong cognitive abilities, but they will never reach their full potential if they are not determined to attend training courses within the organization. In this sense, self-efficacy, courage, motivation, self-control, adaptability, optimism, hope and the ability to cooperate with others become important factors for success for employees in organizations (Bedford et al., 2019; Schneider, Krajcic, Lavonen, & Salmela-Aro, 2020).

2.2 Social Network Analysis

Social network analysis is the application of network science on social networks thus generally it assesses the behavioral patterns of an individual at the micro-level, the patterns of relationships at the macro level and the interaction between the micro and macro levels, (Chee Wei, Juliana, Chuan-Hoo, & Jan, 2014). Thus the social network is a social structure made of actors, which are connected. The strength or intensity of this connection is a measure of the type and or characteristics of the relationship between the actors by one or more. Its representation can be made through a graph where the vertices represent individuals or entities and the edges, the relations among them. Formally a simple social network is modeled as a graph $G = (V, E)$ where: $V = (V1, Vn)$ is the set of vertices or nodes, represented as entities or individuals. $E$ is the set of social relationships, represented as edges in the graph, where $E = (V_i, V_j)|V_i and V_j \in V$ (Akpinar & Gün, 2016; Alhajj & Rokne, 2014; Dubitzky, Wolkenhauer, Cho, & Yokota, 2013; Hock Yeow & Tong-Ming, 2017; Wellman, 1983; Zendejas & Chiasson, 2008), which hinges on the Reductionism Theory; as stated by Barabási, Ravasz, and Oltvai (2003).

Social networks adopt specific indicators to analyze measures such as cohesiveness, centralities, and prestige. Cohesion measures of the network, are considered by researchers as an index of the systematic connectedness of any interactive space. Some indicators of analysis under this general component are, degree, centralization, density, closure, distance, diameter, dependency sum, mutual, breadth (Das, Mahapatra, Samanta, & Pal, 2020; Kuwabara, Zou, Aven, Hildebrand, & Iyengar, 2020; Solomon, 2019; Yousefi Nooraie, EM Sale, Marin, & Ross, 2020; Yrjönkoski, Helander, & Jaakkola, 2016).

2.3 Network characteristics and human capital development

Many studies with different methodologies and scope have researched into the essence of human capital and its development. Romer (1989) in a study assessing the role of human capital in an endogenous economic growth model established that the principal empirical finding is that human capital explains the initial level of rate of investment and indirectly the rate of growth, however, the subsequent impact is dependent on the growth of unique human capital. It further revealed that human capital has no additional explanatory power in a cross-country regression of growth rates on investment and other variables, but consistent with the model, the initial level of human capital does help predict the subsequent rate of investment, and indirectly, the rate of growth. A number of explanatory factors on human capital development such as education, training, research and development, professional new hiring and networking have been undertaken in the field of strategic human capital development.

The micro-level network characteristics of actors’ thus individual employees and aggregately the banks at different spheres of influence on human capital development have been studied at various levels. This characteristics Degree centrality, eigenvector centrality, Betweenness centrality, information centrality and closeness to ideal, (Kong, 2019). Abbasi, Wigand, and Hossain (2014) assessed the human capital and social capital impact on individual performances. The study adopted the social network analysis assessing the major centralities of degree centrality, eigenvector centrality and information centrality on individual performance. The study revealed that the higher an individual’s
centrality the better his or her performance. In a similar study, Daly, Daly, Moolenaar, Der-Martirosian, and Liou (2014) the effect of teacher’s human capital on students’ performance. The study equally adopted the social network analysis approach. In the main, the study assessed the network centralities and cohesion. The study revealed that the characteristics of the teacher in relation to his centralities and cohesion had a positive influence on student’s performance. Stephens (2020) in a study assessing literacy, learning and human capital development among rural African Americans revealed that the network characteristics of centralities influence human capital development. In the main, the study assessed the impact of the various centralities on human capital. The social network analysis and regression were adopted for this study. Further Duncan, Hanney, Burrell, and Rahim (2020) in a study on the integration of technology and human capital development in healthcare established that the social network characteristics of the actors influence healthcare through human capital development processes. In assessing the sustainable development of rural Kazakhstan, Ayulov, Savchenko, Karimov, and Maul (2020), adopted the social network analysis and regression studies in assessing the role of human capital development. The study established that human capital is the most essential factor in obtaining sustainable development within communities. The study adopted the social network analysis and regression for the study.

2.4 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,(Jahanshahloo, Lotfi, & Izadikhah, 2006b; Yoon & Hwang, 1995).

One approach to multi-attribute decision making is the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS),(Behzadian, Otaghsara, Yazdani, & Ignatius, 2012; Lai, Liu, & Hwang, 1994). 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,(Behzadian et al., 2012; Boran, Genç, Kurt, & Akay, 2009; Chou, Yen, Dang, & Sun, 2019; Deng, Yeh, & Willis, 2000), Ecological studies(Amiri et al., 2019; Yong, 2006), Aviation studies(T.-C. Wang & Chang, 2007), Mathematical sciences(Jahanshahloo, Lotfi, & Izadikhah, 2006a) and Engineering (Y.-M. Wang & Elhag, 2006).

3.0 Methodology

The study adopts a mixed-method and social network approach which conceptualizes, develops, mix and intersects diverse approaches, concepts, and tools for reaching conclusion on a study. The study, therefore, adopted Multi-Attribute Decision Making, TOPSIS, Social network analysis and regressions in ascertaining the impact of actor characteristics on human capital development.

3.1 Data Collection

The study relied heavily on secondary data from the banking network of Ghana. Seven listed banks on the Ghana Stock Exchange (GSE) were used to test our models. This was to ensure credibility as the GSE audit all submitted reports on the state of banks to secure investor and customer confidence (GSE, 2019). The Banks were Access Bank, Agricultural Development Bank, EcoBank, CAL Bank, GCB Bank Limited, Republic Bank formerly HFC Bank Ghana Limited, and Standard Chartered Bank Ghana Limited.
The study will employ a structured questionnaire for the study. From the management team, the study will solicit data on the following attributes to build the social network;
1. Academic qualifications,
2. Post-Secondary institutions attended,
3. Working experience,
4. Professional association
5. Countries worked or schooled for a year or more

3.2 Network Development

The studies adopted social learning within social network theories, which helped in optimizing the role of actors and industries in human capital development. The study used Shannon’s entropy method to find the appropriate weight for each criterion in Multi-Attribute Decision Making (MADM). 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. Figure 1 represents the hypothetical network adopted for the study where employee’s human capital acquisition and diffusion are hinged on his/her association with universities, professional associations, and current bank of operation and countries of association. Employees of different banks still have interaction by virtue of their association in any of the network sources.

Figure 1: Network relations

Universities=Uni. Professional Association =Prof. Countries of association= Ctry, Current Bank=Bnk. And Employee/Actors= Emp.

3.3 Variables and their attribute value determination

We adopted our weighting system in our earlier paper, Kong (2019) as presented in Table 1.

Table 1: Variable Selection and description

<table>
<thead>
<tr>
<th>Variables</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Academic qualification</td>
<td>It was detected from the data that the minimum academic qualification was a bachelor’s degree and the highest was a Ph.D. Since these academic qualifications are hierarchically ranked from Bachelor’s Degree, Master’s Degree and Ph.D., raw scores from 1 to 3 were assigned to them. In a situation where individuals had more than 1 academic qualification, the sum of the individual qualifications was considered as the total academic score of the person.</td>
</tr>
<tr>
<td></td>
<td>$A = \sum_{i=1,2,3} a_i$</td>
</tr>
<tr>
<td></td>
<td>Where</td>
</tr>
<tr>
<td></td>
<td>$a$ = Corresponding academic qualification score</td>
</tr>
<tr>
<td></td>
<td>$A$ = Total Score obtained on individual academic qualifications</td>
</tr>
<tr>
<td></td>
<td>$i$ = Individual scores of the academic equation</td>
</tr>
<tr>
<td>2. Educational</td>
<td>In the scoring of schools (universities), the Times Higher Education Ranking was used. The</td>
</tr>
</tbody>
</table>
Institutions attended

Times Higher Education was adopted because it is a global university performance table that judges research-intensive universities across all of their core missions: teaching, research, knowledge transfer and international outlook. The ranking uses 13 carefully calibrated performance indicators to provide the most comprehensive and balanced comparisons trusted by students, academicians, university leaders, industries and government.

This is expressed as;

\[ S = \sum_{i=1}^{n} \sum_{j=1}^{m} U_{ij} \]

Decomposing (1), gives:

\[ \sum_{y=1}^{n} S_{i} = \sum_{i=1}^{n} U_{i} \]

Where (1) and (2) are conditionally premised on

\[ S_{i1} = U_{1} + U_{2} + \ldots + U_{in} \] \hspace{1cm} \text{premise 1}
\[ S_{nj} = U_{i1} + U_{i2} + \ldots + U_{in} \] \hspace{1cm} \text{premise 2}

Where

\[ S_{i1} = \text{Total universities an individual has attended}. \]
\[ U_{in} = \text{Individual scores of a University}. \]
\[ i \& j = \text{Universities} \]

3. Countries

The 2017 Global Human Capital Index was adopted. The ranks of the countries that management team members have interacted with for at least a year (worked and schooled in) were extracted and inversely scored.

\[ B = \sum_{i=1}^{n} \sum_{j=1}^{m} X_{ij} \]

Decomposing (1), gives:

\[ \sum_{y=1}^{n} B_{i} = \sum_{i=1}^{n} X_{i} \]

Where (3) and (4) are conditionally premised on

\[ B_{i1} = X_{11} + X_{12} + \ldots + X_{in} \] \hspace{1cm} \text{premise 1}
\[ B_{nj} = X_{i1} + X_{i2} + \ldots + X_{in} \] \hspace{1cm} \text{premise 2}

Where

\[ B_{i1} = \text{Total countries an individual has visited}. \]
\[ X_{in} = \text{Individual scores of a country}. \]
\[ i \& j = \text{Countries} \]

4. Experience

The work experience attributed coefficient of an actor within this study was derived as

\[ E = E(x) = n \]

Where

\[ E = \text{Total scores of Experience} \]
\[ n = \text{Number of years of experience} \]

5. Professional Association

A point was allocated per association such that the total number of professional association points scored was commensurate of the total number of associations an actor listed membership of on his or her CV. This is aptly represented as;

\[ P = \sum_{i=1}^{n} \sigma_{i} \]

Where:

\[ P = \text{Total scores for a professional association} \]
\[ \sigma = \text{Professional qualifications} \]
\[ i = \text{Individual scores of professions} \]

Source: (Kong, 2019)

The multi-attribute coefficient is, therefore, the total score of an individual (Z) on the variables of assessment as determined in equations 3.1, 3.2, 3.4, 3.6, and 3.7, is a simple summation expressed as
\[ Z_i = \sum_{i}^{n} (S + B + E + A + P) \]

The weight \( W_i \) of an actor in the network was, therefore, a normalized adopted the approach of Jiang, Zeng, Liu, and Ma (2019) which expressed as

\[ \sum_{i=1}^{n} w_i = 1 \]

4.0 Results

Figure 2 represents the network attributes of the banks. The normalized average Degree of the centrality of the general network is 0.043. The normalized average Betweenness of the general network is 0.186. Further the normalized average Eigenvector centrality of the general network is 0.115. Information centrality results indicate a normalized average of 0.256. The slope of Degree Centrality and Betweenness is 0.055 and that of Eigen Vector Centrality and Information Centrality is 1.732

Figure 2: General Network Attributes based MADM

Figure 3 represents a pictorial view of human network connections of the listed banks in Ghana.
Figure 3: Financial Human Capital Network

Source: Field data by authors
4.1 Network Efficiency model

Efficiency in general measures how efficient exchanges of information take place within a network. Thus efficiency quantifies the exchange of information across the whole network or a defined part of the network where information is exchanged. The local efficiency measures how efficient information is exchanged within the egonet whiles global efficiency measures the flow of information within the entire network. Latora and Marchiori (2001) efficiency models will be employed.

Local efficiency of a network is defined as;

\[
E(HC) = \frac{1}{n(n-1)} \sum_{i \neq j \in G} \frac{1}{d(i,j)}
\]

Where \( n \) is the total nodes in a network and \( d(i,j) \) is the length of the shortest path between a node \( i \) and another node \( j \).

Global efficiency of a network will be assessed as;

\[
E_{\text{globe}}(H) = \frac{E(HC)}{E(HC_{\text{ideal}})}
\]

Where \( HC_{\text{ideal}} \) is the ‘ideal’ graph on \( n \) nodes where all possible flows are present. Thus this measure of efficiency takes into consideration a situation where all nodes exchange information with each other but not only the average path length only.

4.2 A Comparative Assessment of Network Attributes and Efficiency

This section of the study explored the relationship between network density, betweenness and information centrality, and efficiency. The in-depth knowledge about the network and its efficiency is critical to adequate in making an informed decision. The network efficiency is
a measure of how efficiently the exchange of information among and within actors are in a competitive space, (Nistor, Pickl, Raap, & Zsifkovits, 2019).

Figure 4: Efficiency and Network Density

The network had an average degree connection of 8.01 with an average density of 0.566 at an efficiency of 0.598. In reference to Figure 4, the circled area depicts the point at which density and efficiency were at equilibrium. The figure again generally showed an inverse relationship between efficiency and density, thus as the network became denser, the flow of knowledge or information required to develop human capital declined. This is typical of a financial network where competition within and amongst institutions vis-à-vis corporate governance structures restrict the share of human capital across institutions (Colbert, 2004; Jawor-Joniewicz & Sienkiewicz, 2016; Merriman, 2017)

Figure 5: Betweenness centrality and Efficiency
The betweenness centrality measures the role of actors as mediators in human capital development. Figure 5 presents the results of the betweenness centrality and efficiency of the network in human capital development. The average betweenness centrality was 0.4. From the clinical look at the points marked in green indicates that as betweenness centrality increases efficiency equally increase. Thus there is a positive relationship between efficiency and betweenness centrality. Freeman (1977) expressed that the betweenness centrality of a knowledge-based network is usually positively related to the efficiency of the network.

Figure 6: Information centrality and efficiency
The study assessed the relationship between human capital development efficiency of the banking network and information centrality. The average information centrality is 0.256. Figure 6 indicates that efficiency fell with time as information centrality remained steady. However, efficiency rose at equilibrium levels as indicated by the marked green circle. The results are supported by Mahsud, Yukl, and Prussia (2011) when they posited that static rate of information movement within a network over time decreases the efficiency of the network in improving human capital development as all actors would have gotten to their steady-state and started declining.
4.3 TOPSIS derived attribute (Closeness to ideal)

The study explored the social cohesion approach of an attribute measure that combined the various attributes of the actors in the network. The approach therefore rationally adopted in multi-attribute decision-making options is the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), (Behzadian et al., 2012; Lai et al., 1994). 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, (Behzadian et al., 2012; Boran et al., 2009; Chou et al., 2019; Deng et al., 2000), Ecological studies(Amiri et al., 2019; Yong, 2006), Aviation studies(T.-C. Wang & Chang, 2007), Mathematical sciences(Jahanshahloo et al., 2006a) and Engineering (Y.-M. Wang & Elhag, 2006)

4.3.1 Approach

The data to be obtained from the banking network $E_{ij}$ 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

$$M = r_{ij} = \frac{E_{mn}}{\sqrt{\sum_{i} E_{ij}^2}}, i = 1, ..., m; j = 1, ..., n$$

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 $F_{ij}$ is developed with a weighted $w$ matrix

$$F = h_{ij} = w_{j} \times r_{ij}, i = 1, ..., m'j = 1, ..., n$$

But $w_{j} = \frac{1}{n}$ and the weight of $j$ actors remains the 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, Medo, Zhang, and Zhou (2017)

$$A^+ = \{h_1^+, h_2^+, ..., h_n^+\} = \{(\max_{P \in K_b} (\max_{i} P \setminus j \in K_c))\}$$

$$A^- = \{h_1^-, h_2^-, ..., h_n^-\} = \{(\max_{P \in K_b} (\max_{i} P \setminus j \in K_c))\}$$

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
\[
S_i^+ = \sum_{j=1}^{n} (h_{ij}^+ - h_{ij})^2, \quad i = 1, ... m; j = 1, ..., n
\]

\[
S_i^- = \sum_{j=1}^{n} (h_{ij}^- - h_{ij})^2, \quad i = 1, ... m; j = 1, ..., n
\]

Finally, the relative closeness to the idea solution \( S \) as a means of determining influential diffusers can be derived from Equation 4.5 and Equation 4.6 as

\[
Q_i = \frac{S_i^-}{S_i^+ + S_i^-}, \quad i = 1, ..., m
\]

The final output from equation 11 was then ranked and used as the optimal influence of industry and actors in the network.

<table>
<thead>
<tr>
<th>Actor</th>
<th>DC</th>
<th>DCRank</th>
<th>EVC</th>
<th>EVCRank</th>
<th>BC</th>
<th>BCRank</th>
<th>IC</th>
<th>ICRank</th>
<th>Ci</th>
<th>CIRank</th>
</tr>
</thead>
<tbody>
<tr>
<td>BC-GCB</td>
<td>0.059</td>
<td>10</td>
<td>0.056</td>
<td>26</td>
<td>5</td>
<td>3</td>
<td>2.68</td>
<td>15</td>
<td>0.43</td>
<td>18</td>
</tr>
<tr>
<td>CAE-ADB</td>
<td>0.031</td>
<td>44</td>
<td>0.042</td>
<td>38</td>
<td>0.353</td>
<td>55</td>
<td>2.56</td>
<td>41</td>
<td>0.29</td>
<td>48</td>
</tr>
<tr>
<td>CFO-ADB</td>
<td>0.031</td>
<td>44</td>
<td>0.037</td>
<td>47</td>
<td>1.258</td>
<td>37</td>
<td>2.535</td>
<td>46</td>
<td>0.28</td>
<td>52</td>
</tr>
<tr>
<td>CFO-EC</td>
<td>0.039</td>
<td>34</td>
<td>0.049</td>
<td>32</td>
<td>1.444</td>
<td>34</td>
<td>2.595</td>
<td>32</td>
<td>0.41</td>
<td>22</td>
</tr>
<tr>
<td>CFO-GCB</td>
<td>0.028</td>
<td>50</td>
<td>0.037</td>
<td>47</td>
<td>0.577</td>
<td>50</td>
<td>2.528</td>
<td>48</td>
<td>0.29</td>
<td>51</td>
</tr>
<tr>
<td>CFO-SCB</td>
<td>0.05</td>
<td>20</td>
<td>0.189</td>
<td>9</td>
<td>0.663</td>
<td>46</td>
<td>2.683</td>
<td>14</td>
<td>0.37</td>
<td>36</td>
</tr>
<tr>
<td>CIO-SCB</td>
<td>0.094</td>
<td>3</td>
<td>0.27</td>
<td>3</td>
<td>2.058</td>
<td>23</td>
<td>2.774</td>
<td>2</td>
<td>0.49</td>
<td>3</td>
</tr>
<tr>
<td>CM-GCB</td>
<td>0.023</td>
<td>56</td>
<td>0.029</td>
<td>55</td>
<td>0.284</td>
<td>57</td>
<td>2.452</td>
<td>56</td>
<td>0.20</td>
<td>61</td>
</tr>
<tr>
<td>COO-EC</td>
<td>0.041</td>
<td>31</td>
<td>0.038</td>
<td>45</td>
<td>2.308</td>
<td>17</td>
<td>2.567</td>
<td>40</td>
<td>0.43</td>
<td>16</td>
</tr>
<tr>
<td>COO-GCB</td>
<td>0.034</td>
<td>41</td>
<td>0.044</td>
<td>34</td>
<td>1.246</td>
<td>38</td>
<td>2.569</td>
<td>38</td>
<td>0.38</td>
<td>31</td>
</tr>
<tr>
<td>CRCO-ADB</td>
<td>0.053</td>
<td>18</td>
<td>0.055</td>
<td>27</td>
<td>2.626</td>
<td>15</td>
<td>2.658</td>
<td>20</td>
<td>0.42</td>
<td>21</td>
</tr>
<tr>
<td>CRO-SCB</td>
<td>0.105</td>
<td>1</td>
<td>0.303</td>
<td>2</td>
<td>3.434</td>
<td>10</td>
<td>2.773</td>
<td>3</td>
<td>0.53</td>
<td>2</td>
</tr>
<tr>
<td>CS-HFC</td>
<td>0.021</td>
<td>61</td>
<td>0.027</td>
<td>59</td>
<td>0.603</td>
<td>49</td>
<td>2.411</td>
<td>60</td>
<td>0.30</td>
<td>46</td>
</tr>
<tr>
<td>DHRB-AB</td>
<td>0.041</td>
<td>31</td>
<td>0.057</td>
<td>24</td>
<td>2.154</td>
<td>19</td>
<td>2.621</td>
<td>29</td>
<td>0.37</td>
<td>35</td>
</tr>
<tr>
<td>DIR2-GCB</td>
<td>0.051</td>
<td>19</td>
<td>0.07</td>
<td>17</td>
<td>4.932</td>
<td>4</td>
<td>2.717</td>
<td>5</td>
<td>0.44</td>
<td>9</td>
</tr>
<tr>
<td>DIR3-GCB</td>
<td>0.047</td>
<td>24</td>
<td>0.05</td>
<td>30</td>
<td>2.796</td>
<td>13</td>
<td>2.617</td>
<td>30</td>
<td>0.43</td>
<td>17</td>
</tr>
<tr>
<td>DIR-GCB</td>
<td>0.087</td>
<td>4</td>
<td>0.059</td>
<td>22</td>
<td>9.656</td>
<td>1</td>
<td>2.652</td>
<td>22</td>
<td>0.49</td>
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</tr>
<tr>
<td>DMD-ADB</td>
<td>0.059</td>
<td>10</td>
<td>0.062</td>
<td>21</td>
<td>2.33</td>
<td>16</td>
<td>2.687</td>
<td>13</td>
<td>0.44</td>
<td>8</td>
</tr>
<tr>
<td>EDBD-AB</td>
<td>0.055</td>
<td>14</td>
<td>0.066</td>
<td>20</td>
<td>3.399</td>
<td>11</td>
<td>2.671</td>
<td>18</td>
<td>0.44</td>
<td>11</td>
</tr>
<tr>
<td>EDCL-EC</td>
<td>0.028</td>
<td>50</td>
<td>0.03</td>
<td>53</td>
<td>0.611</td>
<td>48</td>
<td>2.488</td>
<td>52</td>
<td>0.30</td>
<td>43</td>
</tr>
<tr>
<td>FP-GCB</td>
<td>0.028</td>
<td>50</td>
<td>0.035</td>
<td>51</td>
<td>3.06</td>
<td>12</td>
<td>2.48</td>
<td>53</td>
<td>0.30</td>
<td>45</td>
</tr>
<tr>
<td>GC-ADB</td>
<td>0.025</td>
<td>55</td>
<td>0.029</td>
<td>55</td>
<td>0.231</td>
<td>59</td>
<td>2.473</td>
<td>55</td>
<td>0.20</td>
<td>62</td>
</tr>
<tr>
<td>GHAF-ADB</td>
<td>0.03</td>
<td>48</td>
<td>0.033</td>
<td>52</td>
<td>0.17</td>
<td>61</td>
<td>2.528</td>
<td>48</td>
<td>0.18</td>
<td>63</td>
</tr>
<tr>
<td>Source: Field data processed with UCINET.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------------------------------------</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Degree Centrality (DC), Eigenvector Centrality (EVC), Betweenness Centrality (BC), Information Centrality (IC), Closeness to the ideal (CI).</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

http://www.ijmsbr.com
Table 2 represents the centrality measures and actor ranking of importance in each attribute measure. From the table, there was a significant difference between actors and their importance in the different individual importance measures. For instance, BC-GCB ranked 10th in degree centrality which measures the number of actor connections, 26th position when it came to eigenvector centrality which measured actors relative importance based on the number of high indexed actors that are connected to. Again same actor ranked 3rd position when it came to betweenness centrality that assesses the mediating role of actors in the dissemination of human capital in the network. Justifiably each of the attributes measured specific dimensions of influence and as such applicable for specific needs. The introduction of the Closeness to ideal centrality that takes into consideration the aggregated influence of an actor taken into consideration an optimization view. The Table 2 shows the Managing Director of SCB (MD-SCB) was ranked as the most influential (1st) in the closeness to the ideal that is an aggregation of all the other measures considering the strength and weaknesses of actors in optimizing their rank but 39th in information centrality an individual attribute measure.

### 4.4 Impact of Actor Attributes on Human Capital Development

We further assessed the impact of the actor attributes on human capital development. The independent variables, therefore, included Degree Centrality (DC), Eigenvector centrality (EVC), Betweenness Centrality (BC), Information Centrality (IC) and Closeness to the ideal (CI).

The dependent variable was human capital development (HCD). Return on asset (ROA) was adopted as the proxy for measuring human capital development. Human capital development has been cited in many studies as a major explanatory variable for performance, (Crook, Todd, Combs, Woehr, & Ketchen Jr, 2011; Daniels, 1993; Dass & Chelliah, 2019; Jawor-Joniewicz & Sienkiewicz, 2016; Mahsud et al., 2011; Marimuthu, Arokiasamy, & Ismail, 2009). In these studies, Return on Asset (ROA) was used as an indicator of performance. Return on Asset measures the earnings generated from invested capital. Thus ROA does not only report on earnings but gives clues as to how effective the organization is in converting the money it invests into income, (Jewell & Mankin, 2011). This is a sure indication of human capital development as efficiency in decision making and general management comes to play. The study, therefore, adopted ROA as a proxy to measure human capital development.

In examining the impact of DC, EVC, BC, IC, and CI on HCD, we write our HCD estimate function as:

\[
HDC = (DC, EVC, BC, IC and CI)
\]

Therefore our multivariate \(HCD\) function for our natural log model is given by:

\[
HCD = \beta_0 + \beta_1 DC + \beta_2 EVC + \beta_3 BC + \beta_4 IC + \beta_5 CI + \epsilon
\]

Where \(\beta_0\) stands for the slope coefficient and \(\epsilon\) for the error term. \(\beta_1, \beta_2, \beta_3, \beta_4\), and \(\beta_5\) are the coefficients for DC, EVC, BC, IC, and CI.

The same model was used to run all 7 banks in the network. Ordinary least squares regression (OLS) of the centrality explanatory variable was used to determine the magnitude and direction of effect on human capital development.

*Table 3: Model Summary*
1. Predictors: (Constant), Degree Centrality, Eigenvector Centrality, Betweenness Centrality, Information Centrality, and Closeness to Ideal.

Table 3 represents the model summary where results were organized per bank. The model indicates that GCB had the least R-Square value (0.583) 58.3% with ACCESS having the highest variation (R-Square 0.825) 82.5% in human capital development as explained by the 5 predictors. Akossou and Palm (2013) state that a model with R-Square of above 3 is strong and predictive enough for assessing variation impact on a dependent variable. The 7 models all met the threshold for explanatory variation acceptance(Gordon, 2012). Further, the Dubin-Watson shows that the assumption of independent error is was validated since the values were close to 2, (Watson & Durbin, 1951).

Table 4: ANOVA Table

<table>
<thead>
<tr>
<th>Model</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADB</td>
<td>221.550</td>
<td>5</td>
<td>44.310</td>
<td>7.307</td>
<td>0.009b</td>
</tr>
<tr>
<td>GCB</td>
<td>42.450</td>
<td>7</td>
<td>6.064</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACCESS</td>
<td>264.000</td>
<td>12</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HFC</td>
<td>179.292</td>
<td>5</td>
<td>35.858</td>
<td>4.148</td>
<td>0.018b</td>
</tr>
<tr>
<td>SCB</td>
<td>25.930</td>
<td>3</td>
<td>8.6433</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ECOBANK</td>
<td>205.222</td>
<td>8</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CALBANK</td>
<td>179.932</td>
<td>5</td>
<td>35.986</td>
<td>5.281</td>
<td>0.025b</td>
</tr>
<tr>
<td></td>
<td>34.068</td>
<td>5</td>
<td>6.814</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>208.000</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>127.999</td>
<td>5</td>
<td>25.599</td>
<td>5.296</td>
<td>0.009b</td>
</tr>
<tr>
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<td>14.500</td>
<td>3</td>
<td>4.8330</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>142.499</td>
<td>8</td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>908.651</td>
<td>5</td>
<td>181.730</td>
<td>13.926</td>
<td>0.000b</td>
</tr>
<tr>
<td></td>
<td>91.349</td>
<td>7</td>
<td>13.050</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
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<td>5</td>
<td>17.993</td>
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<tr>
<td></td>
<td>9.034</td>
<td>3</td>
<td>3.011</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>99.000</td>
<td>8</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The Table 4 shows the ANOVA table for the multi-regression per bank. The Analysis of Variance (ANOVA) table indicates that all seven models (ADB, F=7.307; Sig. =0.009, GCB, F=4.148; Sig. =0.018, ACCESS, F=5.281; Sig. =0.025, HFC, F=5.296; Sig. =0.009, SCB, F=13.926; Sig. =0.000, ECOBANK, F=5.975; Sig. =0.012, CALBANK, F=4.914; Sig. =0.009) have a statistically significant effect on human capital development outcomes.

Table 5: Coefficients

<table>
<thead>
<tr>
<th>Model for individual bank</th>
<th>Unstandardized Coefficients</th>
<th>Standardized coefficients</th>
<th>Collinearity Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>Std. Error</td>
<td>Beta</td>
</tr>
<tr>
<td>Constant</td>
<td>12.168</td>
<td>0.198</td>
<td>4.899</td>
</tr>
<tr>
<td>DC</td>
<td>32.951</td>
<td>0.658</td>
<td>2.551</td>
</tr>
<tr>
<td>EVC</td>
<td>41.157</td>
<td>0.563</td>
<td>-0.433</td>
</tr>
<tr>
<td>ADB BC</td>
<td>37.034</td>
<td>0.024</td>
<td>0.802</td>
</tr>
<tr>
<td>IC</td>
<td>154.757</td>
<td>0.861</td>
<td>1.290</td>
</tr>
<tr>
<td>Ci</td>
<td>311.062</td>
<td>0.063</td>
<td>1.130</td>
</tr>
<tr>
<td>Constant</td>
<td>7.321</td>
<td>0.582</td>
<td>6.752</td>
</tr>
<tr>
<td>DC</td>
<td>24.597</td>
<td>0.895</td>
<td>1.461</td>
</tr>
<tr>
<td>EVC</td>
<td>43.949</td>
<td>1.650</td>
<td>1.520</td>
</tr>
<tr>
<td>GCB BC</td>
<td>122.050</td>
<td>0.051</td>
<td>1.806</td>
</tr>
<tr>
<td>IC</td>
<td>201.366</td>
<td>2.607</td>
<td>1.503</td>
</tr>
<tr>
<td>Ci</td>
<td>353.004</td>
<td>0.130</td>
<td>-0.049</td>
</tr>
<tr>
<td>Constant</td>
<td>20.029</td>
<td>0.335</td>
<td>2.087</td>
</tr>
<tr>
<td>DC</td>
<td>40.325</td>
<td>0.704</td>
<td>-0.835</td>
</tr>
<tr>
<td>EVC</td>
<td>53.090</td>
<td>0.090</td>
<td>-0.646</td>
</tr>
<tr>
<td>ACCESS IC</td>
<td>320.018</td>
<td>0.019</td>
<td>0.625</td>
</tr>
<tr>
<td>IC</td>
<td>230.136</td>
<td>1.463</td>
<td>0.173</td>
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<tr>
<td>Ci</td>
<td>235.050</td>
<td>0.166</td>
<td>0.672</td>
</tr>
<tr>
<td>Constant</td>
<td>4.174</td>
<td>0.004</td>
<td>4.801</td>
</tr>
<tr>
<td>DC</td>
<td>13.999</td>
<td>0.021</td>
<td>3.668</td>
</tr>
<tr>
<td>EVC</td>
<td>29.105</td>
<td>0.005</td>
<td>0.446</td>
</tr>
<tr>
<td>HFC CI</td>
<td>173.016</td>
<td>0.000</td>
<td>0.743</td>
</tr>
<tr>
<td>IC</td>
<td>212.862</td>
<td>0.017</td>
<td>3.334</td>
</tr>
<tr>
<td>Ci</td>
<td>313.002</td>
<td>0.001</td>
<td>0.051</td>
</tr>
</tbody>
</table>
Table 5 represents the results from the multi-collinearity test and beta values for the independent variables. From Table 5, no incidences of multi-collinearity were identified in the model as all the variance inflation factors were within acceptable below 5 range (Alin, 2010). The variables in regards to the model specified indicate that each variable has a statistically significant impact on the dependent variable for each bank. A clinical look at the explanatory variables Closeness to the ideal (CI) showed a stronger significance comparatively in all the individual banks to the other individual centralities.

5.0 Discussions and conclusion

The variability of the possession of the needed human capital and the ability of actors to transfer knowledge in institutional networks is of major concern in modern times for competitiveness and institutional performance. The study assessed the role of individual actors and banks in human capital development. The study adopted network analysis and ordinary least square regression (OLS) to ascertain the magnitude and direction of effect of the explanatory variables and dependent variables. The study first measured the efficiency of the human capital network and assessed the key attributes of the network to efficiency. Again the study introduced an integrated social cohesion methodology that assesses an optimal unifying centrality base on the multi-attribute dimension model (MADM) and finally regressed the centralities on human capital to ascertain their relative statistical significance in both magnitude and directional effect.

From the results, the study established that the network was 59.8% efficient in human capital development. The study, however, revealed that there was an inverse relationship between efficiency and density. Thus the denser the network the less effective the network becomes towards human capital development. This is typical of banking networks where competition within and amongst institutions with corporate governance structures
restricts knowledge sharing (Ferris, Javakhadze, & Rajkovic, 2017). Further, the mediating role of actors (betweenness centrality) was compared to network efficiency. The results indicate a positive relationship as betweenness centrality increases so do human capital development networks increases. Betweenness in networks marks extension and linkages to sources of knowledge that might have eluded the network if a particular actor has not played a bridge role. Finally, on attribute comparison with network efficiency, the study assessed the information centrality and network efficiency. The results showed that network efficiency falls over time when information centrality does not increase or remain steady over a longer period of time. This is a clear implication of the need to constantly through policies and practices keep information inflow and growth through activities like research and development to improve the efficiency of the network.

Finally, in the study assessing the role of actors in human capital development, the 5 attributes were regressed on human capital development to ascertain their impact. The variables in regards to the model specified indicate that each variable has a statistically significant impact on the dependent variable for each bank. A clinical look at the explanatory variables Closeness to the ideal (CI) showed a stronger significance comparatively in all the individual banks to the other individual centralities. This implies that the individual characteristics had a unique impact on human capital development; namely degree centrality, betweenness centrality, eigenvector centrality, and information centrality, however, the composite optimized centrality, closeness to ideal was statistically more significant.

The study in light of the findings and discussion concludes that network characteristics of actors’ impact on human capital development in the banking network of Ghana. In addition as network density increases, the efficiency of the network in human capital development decreases.

Implication for Policy
The following recommendations are made in light of the findings and conclusion;

1. Banks should engage in networking activities to enhance their human capital, however, greater attention should be paid to the egonet where efficiency in human capital development will increase. As the finding indicated the denser a network become the less efficient it becomes in human capital development. Focusing more on local networks (Egonet) that will have a lesser density will impact more on human capital development which will secure the unique human capital needs of specific banks as well as benefiting from the generic knowledge of the industry in the general network.

2. We recommend that human resource managers in their selection of employees take into the fitness role of the employee within the ego net in terms of their centrality roles in human capital development. However, in the situation of cost-effectiveness, the closeness to ideal optimization centrality should be adopted in poaching an all-round centralized human resource in human capital development capability.

3. Finally, a constant and renewable source of information through activities of research and development, professional networking participation, both on the job and off the job training activities should be factored in policies of institutions to enhance human capital development at organizational levels.

References


