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Know Your Stars Before They Fall Apart: A Social Network Analysis of Telecom Industry to Foster Employee Retention Using Data Mining Technique

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ABSTRACT Social network analysis (SNA) has emerged as a significant paradigm for research in data mining community for measuring and analyzing human dynamic network structure. At organizational level, SNA can enhance our understanding of work place social interactions and unveil the hidden stars embedded in informal networks by investigating nodes and edges of complex networks. For this study, we aim to formulate a network centrality based quantitative method to identify the High potential employees (HiPos) and Influencers of telecom sector and explore the relationship between degree centrality of these star employees and their turnover intention by modeling the dynamics of their workplace social ties and predictive data mining technique. We investigated the multiplex work and advice network in two leading telecom operators of Pakistan i.e. Ufone and Zong. For the statistical analysis we conducted a quantitative and visual network analysis in UCINET along with correlation and regression. Our results showed a negative correlation between HiPos out-degree centrality and turnover intention and a positive correlation between influencer's in-degree centrality and turnover. Whereas perceived investment in employee development (PIED) was found to mediate the relationship between in-degree centrality of influencer and turnover intention. The correlation results were then verified in regression model. These findings will guide the telecom operators in designing an optimal structure for business intelligence by providing critical insights of their star employees and help them to investigate the influence of central nodes on dynamical processes of its heterogeneous networks and thus enhance employee retention before a star falls out.

INDEX TERMS Social network analysis, data mining, in-degree centrality, out-degree centrality, HiPo, influencer, employee retention.

I. INTRODUCTION

Employees are the intellectual resource for any organization, and are a key contributor of business success [1]. Given the paramount value of employees in today's competitive knowledge economy, human resource management is always on the look to attract and retain them [2]–[4]. However every employee is unique, having varying set of personal skills and capabilities and contribute differently to organizational success. Some may be more motivated than others, some may be more influential, some employees tend to be more social while some may be hard-workers with no social skills. Taken together, these are the hidden gems or stars working across all hierarchies of the organization [5], [6]. Identifying and retaining your best talent is important for businesses [7]. This is especially crucial for Pakistan's telecom industry because this sector is soon going to experience a major shift in technology with the introduction of 5G, IoT (Internet of things) and artificial intelligence in the near future. This changing face of the industry will not only transform the business models but it will also impact all the stake holders of this sector. In comparison to the employment opportunities of the past, employees will now have wider job avenues to switch. Already, voluntary turnover and employee retention has been a perennial issue for this industry and with the introduction of new technology, this problem will further escalate. Statistics show that for career progression, employees in this industry are prone to switch their jobs more frequently than any

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other industry of the country. Telecom operators will be at great risk of losing their star performers who are critical for business success. Owing to this context, there is a great need to identify the star employees of telecom industry and then take preemptive measures to retain them.

To address this issue, we propose to conduct an organizational network analysis (ONA) to identify the key performers of the industry and predict their turnover intention. This study will help the telecom operators in designing an optimal structure for business intelligence by providing critical insights of the star employees who really drive performance in their organization. They can thus timely invest to retain the quality employees before the competitors hire them. But one major challenge in this regard is: *These star employees are not represented in formal organizational chart*. Also the specific employee characteristics of these stars e.g. motivation level of high potential talent and trustworthiness and credibility of influencer employees is difficult to measure through traditional performance evaluation methods like ranking methods and paired comparison etc. The traditional performance evaluation of an employee is usually done by the manager whose judgement might suffer biasness, making these method not only highly subjective but also lack fairness in accessing the real worth of an employee. The above mentioned employee characteristics can only be observed from social interaction with their colleagues at workplace. For such an assessment, either management has to closely monitor each and every employee which is not a realistic approach or they should adopt a more holistic technique like Social Network Analysis [8].

Since employees do not function independently, they co-exist with others in their workplace for day to day tasks. They interact with their colleagues either for advice, work related or for casual friendships, which gives rise to their specific social network. Such interactions form a complex web of connections which can either be formal or informal, reflecting varying interdependency of employees on each other [9]. Structural characteristics of these networks can help to identify the most socially adept and well integrated employees of the organization and can also help to speculate many outcomes including their turnover [10]–[12].

Various network measures can be utilized to find the star employees. The most commonly used social network characteristics are Degree Centrality, Betweenness, Closeness and Eigenvector Centrality. These measures are a significant tool in network theory to identify how central a person is in his social network [13], [14]. The network position of an individual can determine the critical nodes and their influence on organizational social network [15].For example [16] used Graph convolutional network along with nine other network centrality measures to identify HiPos. They found that HiPos are good performers and are more active in building social capital for carrying out their daily tasks. Soares *et al.* [17] used in-degree, out-degree and modularity to identify three different types of influencers, ''opinion leaders'', ''informational influencers'' and the ''activists'' in Brazil. Their results revealed that the modularized networks were closely enmeshed around these influencers. Most of these studies employed different identification methods to spot individuals with certain characteristics within their social networks, yet there is lack of research for network centrality of star employees and turnover.

For this study we focused on two types of star employees; High potential employees (HiPos) and Influencers. HiPos are constant learners, self-motivated and considered to be the future leaders [16], whereas Influencer are the ones whose opinion hold sway with others in their network because of credibility for their knowledge and skill [18]. Pertaining to the significant value of these employees in organizations, it seems logical to identify these employees by employing social network analysis that uses different network parameters to measure the interconnectedness between actors and rank them based on their centralities in their social network. Motivated with this background we propose to develop a network centrality based quantitative method to identify the HiPos and Influencers of telecom sector and explore the relationship between network centrality of these star employees and their turnover intention by modeling the dynamics of their workplace social ties and integrating it with predictive data mining technique. In addition to quantitative network analysis, we propose to employ network visualization using NetDraw for a better understanding of the structural characteristics of heterogeneous organizational social network. We also intend to enhance retention of these star employees by exploring how perceived investment in employee development (PIED) mediates the relationship of social ties of these employee and their turnover intention but it is not the main focus of our study.

Literature reveals that numerous studies have been carried out in the past for organizational network analysis in different industries [19], [20] and [21], however SNA has never been conducted to identify HiPos and Influencers of telecom sector based on their interconnectedness in their network. Despite the availability of wealth of social theory on social network of employees, no theory can be implemented as such since dynamics of every industry is unique with varying goals and objectives making certain postulates less valid. Therefore to bridge this gap, we investigated the workplace social ties in multiplex network of two leading telecom operators of Pakistan namely Ufone and Zong. Both these operators are fighting for their sustainability and organizational excellence due to rigorous competition in the market.Especially in the last few years, with the foray of multinational investments in this sector, rapid technological changes and a cut throat competition has been observed between these two competitors. Statistics show that for career progression, employees in this industry are prone to switch their jobs more frequently than any other industry of the country.

Our study is the first to employ the social network theory to identify high potential employees and influencers using quantitative and visual network analysis to predict voluntary turnover of star employees in telecom sector to foster employee retention. This research empirically investigates the relationship between social ties in multiplex network of work and advice and voluntary turnover in the context of telecom employees which was overlooked in the previous literature of employee retention theory.

The key contribution of this paper are:

1. Application of social network and graph theory on telecom sector.
2. Investigating multiplex work and advice network.
3. HiPo and Influencer identification using network centralities and visual graphs.
4. Using data mining approach for turnover prediction.
5. Investigating the role of PIED on network centrality of star employees and turnover.

The rest of the study is organized in different sections as follows. First we review the existing literature on social network ties and star employees followed by hypothesis of our research. Next we describe our research methodology and data analysis method. Research results and discussion are elucidated in the next section. Finally we conclude our paper with practical implication and future work.

II. THEORY AND HYPOTHESIS DEVELOPMENT

A. ORGANIZATIONAL SOCIAL NETWORK AND TURNOVER

Organizational social network refer to the social structure in which employees are represented as nodes or actors and the type of relationship between them is represented as a tie [9]. In organizations, employees interact with each other at all hierarchies for exchanging information, transfer of knowledge and expertise or for casual chit chats. These workplace interactions form a complex social network which can be formal or informal depending on the type of communication between individuals such as friendship networks, advice network, knowledge networks etc., [22]. However such networks are not easily detectable through formal organizational charts, because how work is actually done in organizations is very different from what is expected from formal job descriptions. Therefore organizations employ social network analysis to understand the inner working of their informal network structure [15].

The pattern of communication of these social networks holds a significant concern in organizational behavior [23]. Therefore, quantifying social network is a critical task in employee turnover context. Bulk of studies on employee turnover state that employees who have higher network centrality in their network, feel more embedded with their organization and they are less likely to quit [24], [12]. Both Feeley *et al.* [24] and Vardaman *et al.* [12] predicted employee turnover in friendship network but they did not account for other networks like work and advice network. Also, these studies neglected the perspective of turnover intention of star employees. In organizations, social networks are rarely that simple, rather they are quiet complex and heterogeneous. To carry out daily tasks, employees usually have a dense work and advice network and these networks are mostly intertwined making it even more complex, which can greatly influence an employee's decision to turnover. The current study attempts to uncover multiplex work and advice network to identify HiPos and Influencers embedded in these networks and predict their turnover, an important element which was over looked in the past.

In a recent research by Kwon [25], turnover prediction for peripheral and marginal employees was discussed using social identity theory. This study suggests that employees who are on the periphery or margin of their organizational network, feel less connected with their organization and have higher quit propensity. In another network study conducted by [20] intended and actual turnover of employees was investigated from psychological and sociological perspective. Their findings suggested that chances of acting upon the intention to leave the current employer is attenuated when employees are central in their advice and friendship network, which is in line with our reasoning for employee network centrality. Other turnover models suggest that having higher out-degree centrality with indirect ties gives easy access to outside information regarding employment opportunities which enables them to switch their jobs more easily [26]. Studies on organizational social network and turnover theory has invoked critical insights into job embeddedness, network position and structural equivalence of employees in organizational social networks [24], [27], [28].

Despite the wealth of turnover theories of organizational networks, none of the studies catered for turnover prediction of the star employees who really drive performance in organizations. To fill this gap, the present study intends to shed light on social network theories of star employees in multiplex work and advice network and turnover theory, offering a unique dimension to the factors fostering employee retention.

B. SOCIAL NETWORK ANALYSIS AND STAR EMPLOYEES

For organizations, contribution of every employee is important however star employees typically have the right attitude to achieve organizational goals. Star employees are those individuals who have outstanding individual productivity and have the competence to create profound effect on firm's value [29]. They vary in their proficiencies and skills and outperform others in their network but they are not reflected in formal organizational hierarchies. Social network analysis can help to identify these hidden stars who are socially adept and well integrated in their organizations [11]. Star employees tend to mitigate the negative relationship of employee turnover and firm's performance [30]. For our paper we focused on two types of star employee's; HiPos or high potential employees and influencer employees. We chose HiPos and Influencers for this study because they are the ones whom organizations want to retain the most [31], [32] because of their competencies.

1) HIPOS

High potential individuals are constant learners, they are hungry for knowledge, they have the aptitude to move upward in the organizational pyramid and become the future leaders of their organization [7], [33]. They are eager to develop new skills and are open to seek guidance on work related matters to accomplish their tasks efficiently. Dries & Gieter [34] investigated the effect of information asymmetry of high potential programs on HiPos and found that an imbalance in financial reward or pay dissatisfaction can be detrimental in retaining high potential individuals. Khoreva and Zalk [35] studied the work engagement of high potential employees in Finnish Multinational enterprises (MNE's). They found that when HiPos are provided with leadership development activities, they reciprocated this investment by their increased work engagement towards their organization. Chamorro-Premuzic *et al.* [36] stated that investing in the high potential employees will maximize organizational profits. References [7], [33], [35] and [36] consider HiPos as strategic asset for the organizations, supporting the notion why it is necessary to retain high potential talent based on their relative proficiencies. However these studies did not account for HiPo identification and neither they predicted their turnover intention, which limits their application for star identification through social networks.

Recently [16] conducted a study to identify HiPos among newly enrolled employees using Graph Convolutional network and social network centrality measures. Their findings revealed that HiPos tend to develop higher social centrality in the organizational networks in order to carry out their daily tasks. Among the above mentioned studies, identifying high potential talent [16], is the most relevant study with our research. However, [16] focuses only on identification of HiPos using graph convolutional network along with employee network centrality, it doesn't cater for their turnover prediction which is the focus of our research. Moreover [16] uses internal email data to construct employee social network but this data collection method cannot comprehend the informal multiplex work and advice network of employees which is the foundation of our study. To cater for this inadequacy, we propose an algorithm to identify star employees using network centrality measures by constructing an adjacency matrix derived from multiplex work and advice network data.

Based on evidence from pasts studies and extending [16] work on HiPo identification, we theorize that since HiPos have higher learning agility and are more motivated, they have higher out-degree centrality in advice network, they go beyond their mandatory work flow network to seek advice on work related matters for their professional development. We hypothesize that when such individuals are able to get the required advice for knowledge and skill outside their work network they feel contented with their work and less compelled to leave their job.

Hypothesis 1: Out-degree centrality of HiPos in advice network outside required workflow is negatively related to turnover intention.

2) INFLUENCERS

Influencer employees in the organization are the ones who are most prominent in their social network, approached the most by their peers for advice, help others to carry out their tasks and are open to share their experiences [38] ; [38].Their peers trust them because they know how to get things done, are action driven and have sound technical knowledge. Studies on influencer nodes reveal that such individuals help in fast information diffusion across their social networks because they are highly connected individuals with a higher degree centrality in their network [39], [40]. In a recent research, Wen and Deng [41] investigated six real world complex networks to identify the influencer nodes using Shannon entropy measure. They found that individuals are more influential when they have a higher centrality in local information dimensionality. These studies suggest that degree centrality of organizational networks is associated with influencers in most of the cases.

Although there are various methods to identify influencer individuals, however, none of the past studies on influencer identification method measured the effect of multiplex work and advice network on turnover intention of influencer employees, which limits there application on social networks for turnover prediction. Among these, the most relevant study to our research problem is Identification of influencers in complex networks, i.e., [41]. But since [41] focuses on local information dimensionality, rather than turnover intention of influencer employees studied in this paper, it cannot be used for turnover studies of organizational networks. To cope with the influencer turnover prediction problem, we formulated a network centrality based quantitative method to identify the most influencer employees from heterogeneous complex network at workplace using social network approach.

Based on the above mentioned studies, we theorize that since influencers have sound technical knowledge and expertise, their colleagues trust their opinion and seek frequent guidance from them for their routine tasks, consequently influencers have higher in-degree centrality in multiplex work-advice network. We argue that in a mandatory workflow network, when influencers are frequently approached for advice from their colleagues whose request they cannot turn down because of work requirement, they feel frustrated since they have to stop what they are currently doing and fulfill the mandatory advice request first. Such individuals have more probability for burnout and can have higher turnover intention.

Hypothesis 2a: In-degree centrality of Influencers in advice network intertwined with required workflow is positively related to turnover intention.

Since advice giving is not a formal job description of influencers, nor this behavior is formally documented with the top management. We suspect that if the managers do not recognize such behaviors by providing influencers with employee development opportunities for career progression, the influencers perceive that their organization is not investing in them. Social exchange theory [42] suggests that when cost of employee effort is higher than the reward, such as extra effort put in by the influencers in the form of advice is not rewarded by the managers, they will feel that their contributions are not valued and they reciprocate by a reduced affective commitment with the organization and a greater intentions to leave. Research shows that perceived investment in employee development is negatively related to employee turnover [43]. Following the social exchange theory (SET) we argue that when influencers perceive that their organization is not investing in employee development, their turnover intention increases.

Hypothesis 2b: PIED will mediate the relationship between in-degree centrality of Influencers and turnover intention.

III. RESEARCH METHODOLOGY

A. CONTEXT AND PARTICIPANTS

We conducted this research within the context of two leading telecom operators of Pakistan namely Ufone and Zong. Ufone is one of the pioneers of GSM cellular service provider in Pakistan and has a subscriber base of 23 million. Whereas Zong is the first telecom operator to launch its 4G service in the country and has already started trials for 5G and has a subscriber base of nearly 34 million. The reason for choosing these two operators was that since Ufone is in the infancy stage of 4G technology, its employees feel obsolete, have less growth opportunities and are prone to turnover. However Zong, despite being the early adopter of 4G technology, now has reached a stagnancy stage and its employees also feel lack of career advancement and the company is facing high employee turnover. Ufone has the lowest 4G market share of 6% whereas Zong has the highest 4G market share of 40% making it worst and best case scenario of the industry.

In an era where telecom players in the rest of the world have already stepped into the digital services like Internet of things (IoT) and artificial intelligence [44], [45] telecom operators in Pakistan are far behind the game. But in the coming few years a major shift is expected towards incorporating the digital lifestyle services alongside 5G, making the employees in both these companies more vulnerable to turnover if proper retention policies are not adopted. These factors make Ufone and Zong a good candidate for our research.

Sample data for this study was collected from employees in Islamabad and Lahore region. Before conducting this survey, network boundaries were identified to capture complete network [46], [47]. We employed whole network data collection method for our research, an approach followed by many researcher in the past [48]; [49]. For network synchronization, employees from only core engineering department from both the operators were selected. However the participants differ in age, tenure and job experience. There were total of 169 employees (74 in *Zong* and 95 in *Ufone*) who participated in our survey.

The employees engaged in different job roles since core engineering is further divided into sub-divisions such as *IN & VAS, Planning and Development, PMO, Roll out*, *RAN, FOPS, Project deployment, NSS and BSS.* All the participants had a basic educational background of bachelors in engineering with varying master's degree in project management and business administration. The participants of this survey were 94% male and 5% female.

B. DATA COLLECTION AND PROCEDURE

For maximum participation of the targeted population, a meeting was arranged with all the employees of engineering department to whom purpose and procedure of this research was explained. To be part of this study, an informed consent was also obtained from each participant. A self-administered questionnaire was developed on Google Form which comprised of social network questions along with other demographic attributes. We used roster-recall method for full network data collection, in which names of all participants of the said department were listed [50]; [51]. Employees were asked to identify their contacts from the list whom they approached for work and advice within their organization.

The survey was carried out in two stages. In the first stage, pilot study was conducted with only 20 employees from Ufone. The aim was to see if participants had any ambiguity in completing the questionnaire with roster method. After receiving a positive response, the actual survey for whole network was executed in second stage. For this stage, all those employees who agreed to take part in this study were sent an email with the link for online survey. After two weeks had elapsed from sending the initial email, three more reminders were sent. Network data collection was completed in 2 months from March 2019 till May 2019.Response rate from both the operators were as follows: Zong 89.2% (66/74) and Ufone 85.3(81/95). The final response rate for this survey was 87% of the network population from two telco's of Pakistan.

C. MEASURES

1) DEMOGRAPHICS

The first part of the survey contained 8 items for general demographics. Participants were asked for their gender, age, department, designation, work experience etc. All the demographics were manually coded for privacy concern of employees.

2) SOCIAL NETWORK QUESTIONNAIRE

Second part of the network survey contained 2 items to collect the sociometric data of employees. Participants were provided with a roster of all employees working in core-engineering department. They then were asked to respond to the questions "Are you required to work directly with this person in order to get your work done" and " Do you go to this person for work related advice and knowledge''. Participants were also encouraged to list down any other employees whom they could recall interacting with, across different departments. This approach follows a name-generator survey method by [52].

3) TURNOVER INTENTION

Turnover intention of the employees was measured by using the Michigan Organizational Assessment Questionnaire, a survey used by [53]. It is a 3 item questionnaire with a 5 point Likert-scale ranging from 1(strongly disagree) to 5 (strongly agree).The Cronbach's alpha of this scale was 0.66. The sample item of this scale were "I often think about quitting," "I will probably look for a new job in the next year," and "How likely is it that you could find a job with another employer with about the same pay and benefits you now have?"

4) PERCEIVED INVESTMENT IN EMPLOYEE DEVELOPMENT

The scale of employee development was taken from the research work of [54].We adopted 4 items with the highest factor loading for our study, measured on a 5 point Likert-scale. The Cronbach's alpha of this scale was 0.743. The sample item of this scale were "My organization trains employees on skills that prepare them for future jobs and career development'', "My organization provides career counseling and planning assistance to employees'', "My organization allows employees to have the time to learn new skills that prepare them for future jobs'', "My organization provides support when employees decide to obtain ongoing training''.

D. DATA ANALYSIS

1) CONSTRUCTING THE SOCIAL NETWORK

To construct social network of employees, an adjacency matrix was developed, based on sociometric questions of who goes to whom in a multiplex network of work and advice. It is a type of square matrix used in graph theory in which all the participants are listed across horizontal and vertical axes, with each row and column representing a single employee interaction [46]. For data confidentiality and anonymity, unique codes were assigned against names of all participants. Initially we created separate square matrices for work and advice. The interaction nominees or relational ties indicated by the employees were represented in binary form against each cell. The presence of a tie was coded as '1' and absence of a tie was coded as '0'.

The representing $n \times n$ square matrix is

$$A = \begin{array}{c} \\ v1 \\ v2 \\ \cdots \\ vn \end{array} \begin{array}{c} \begin{array}{cccc} v1 & v2 & \ldots & vn \end{array} \\ \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix} \end{array} \tag{1}$$

Where vertices v1,v2,...,vn are the nodes(employees)

$$A_{ij} = \begin{cases} 1, & \text{if there is an edge between vertices} \\ & \text{i and j} \\ 0, & \textit{otherwise} \end{cases}$$

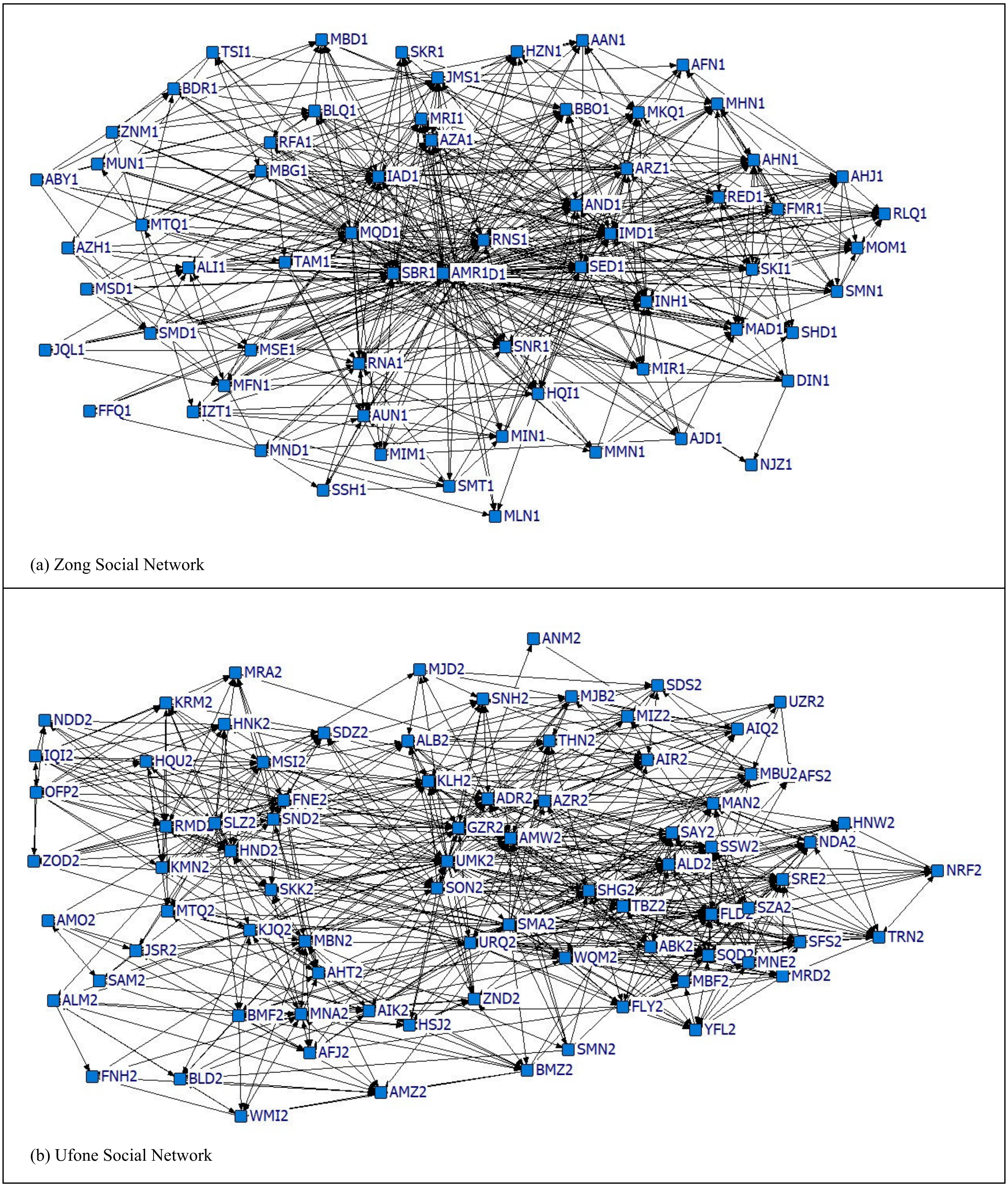
For identifying HiPo's, we were interested in knowing which employee is more enthusiast and goes out of the way to seek advice on work related matters out of his mandatory work flow network. For this we combined the two networks in a single summary matrix in such a way that a cell was assigned a value of one (1) for work only tie where advice tie did not existed, value of two (2) was assigned for advice only tie where work tie did not existed and value of three (3) was assigned for multiplex work and advice ties. Representing the presence of multiplex relations this way illustrates a qualitative typology of employee interactions in a work environment [46]. For our study we focused on the rows containing the number 2. To convert our data again into binary matrix of 1's and 0's, we replaced all values of one and all values of three in the newly created matrix with zero (0) and replaced all values of two with one (1). We now had a matrix with employees in each row seeking advice from employees in the column whom he is not required to work with.

For identifying the influencers, we wanted to know which employee was considered trustworthy and was sought out for advice by others. For this we again combined work and advice network by taking transpose of the advice network and added work matrix to it. Now the value of 2 in the resultant multiplex matrix represented the employees who were most sought out for advice and they had a mandatory work flow tie associated with them as well. To convert the multiplex matrix into binary data, we replaced all other numerical values with zeros (0) and replaced value two with one (1).

We now had two adjacency matrices of employees with multiplex network. The relational ties in our adjacency matrix were asymmetric, since one employee may nominate other employee for work or advice but the other employee may not reciprocate the same.

2) QUANTITATIVE NETWORK ANALYSIS

Social network analysis of the acquired data was done by importing the adjacency matrices in UCINET VI [55] which computed the network centralities for each employee. For our analysis, we computed the degree centrality which is the measure of prominence of the employees in the network [56]. Degree centrality counts the number of ties of a node connected to other nodes of the network. Since it is a directional measure we calculated the out-degree centrality for HiPos and in-degree centralities for influencer identification. The higher the numbers are on degree measure, the more central the employees are in their network [57]. In-degree centrality refers to the number of incoming ties directed towards the focal node whereas out-degree centrality refers to the number of outgoing ties which the focal node directs towards others in their network [58].



(a) Zong Social Network

(b) Ufone Social Network

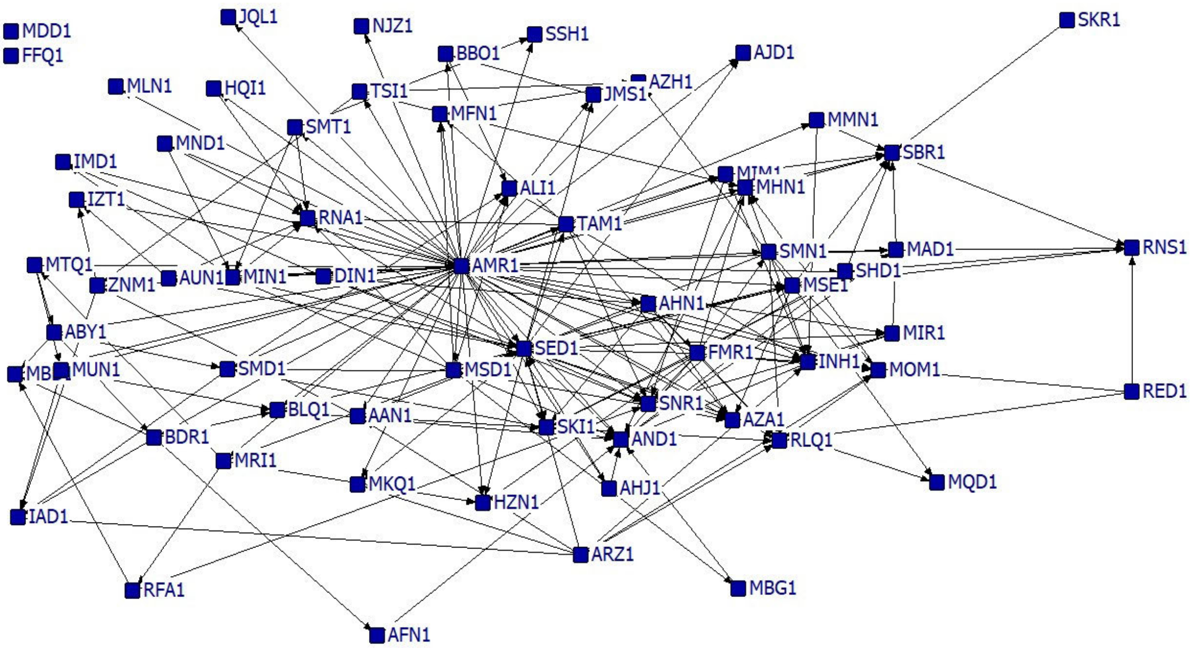
FIGURE 1. Sociogram of employee connections based on multiplex work and advice network.

In-degree centrality = Nominations from others or Number of incoming edges to a vertex.

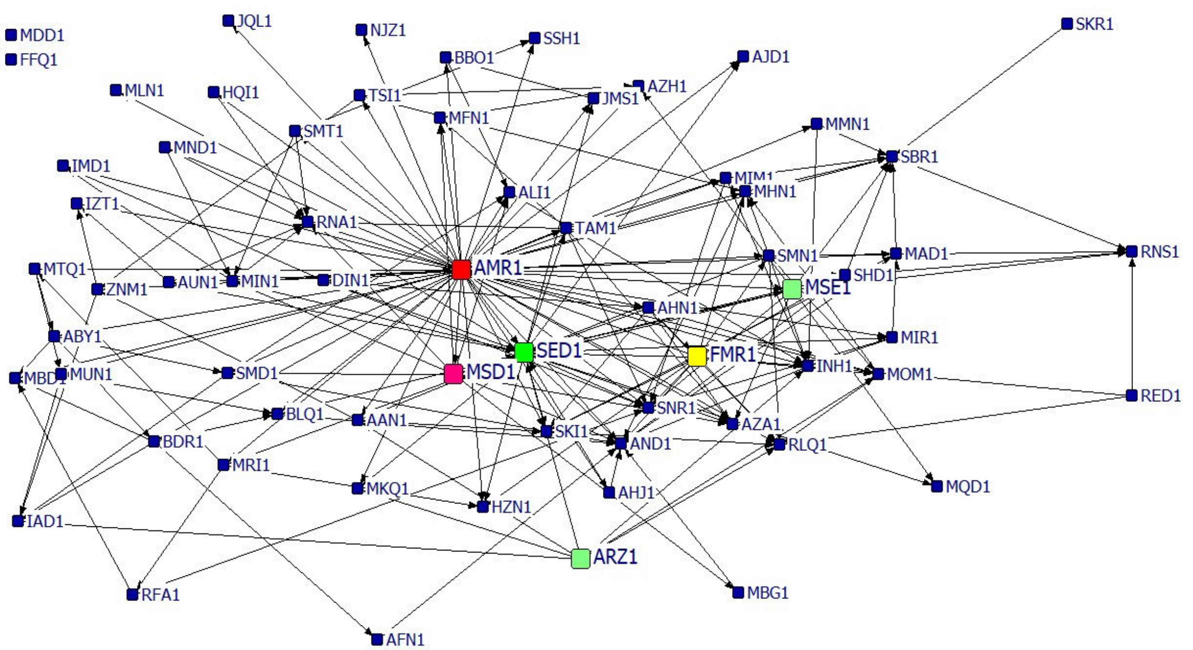
$$C_D^{in} = \sum_{j=1}^{n} A_{ij} \tag{2}$$

Out-degree centrality= Nomination of others or Number of outgoing edges from a vertex

$$C_D^{out} = \sum_{j=1}^{n} A_{ij} \tag{3}$$

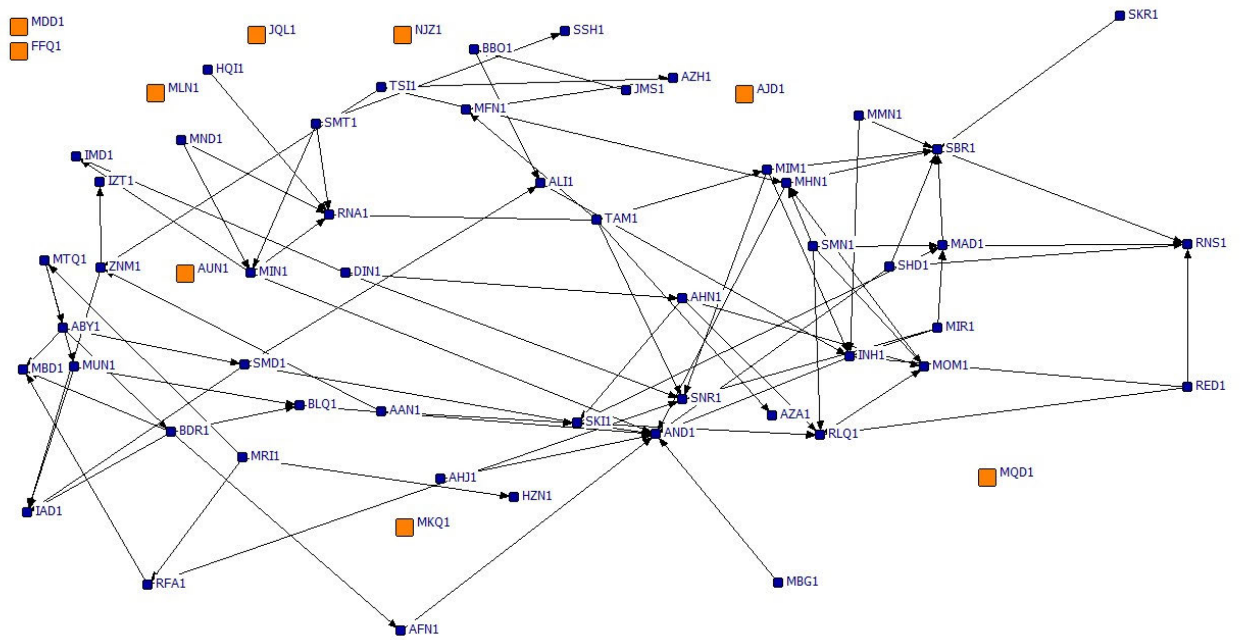


(a) Advice ties outside mandatory workflow



(b) HiPos (red, green, yellow, pink) – Non-HiPos (Blue)

FIGURE 2. Zong Sociogram of Advice ties outside mandatory workflow.



(c) Sociogram without HiPos

*Isolates (Orange)

FIGURE 2. ***(Continued.)*** **Zong Sociogram of Advice ties outside mandatory workflow.**

Where A represents the adjacency matrix, n is total number of employees, i is the focal employee and j represent all other employees.

The resultant network centrality scores were then exported in SPSS to test our hypothesis.

3) NETWORK VISUALIZATION

SNA offers an insightful perspective of relationships of people by providing both visual and mathematical analysis [22]. For our network visualization, network survey data collected from the participants was used to generate network maps or sociograms. The sociograms are comprised of network nodes (actors) and edges (ties or relationships). In our context, employees from core engineering department represent the nodes and their interactions represent edges or ties. Employees interact with each other in a directed multiplex network of work and advice. We used NetDraw 2.161 software for mapping these sociograms [55]. Visual mapping was done to get an idea of the overall interaction of employees in their work and advice network, to understand the prominence of the individuals which will help to correlate and interpret the quantitative parameters.

IV. RESULTS

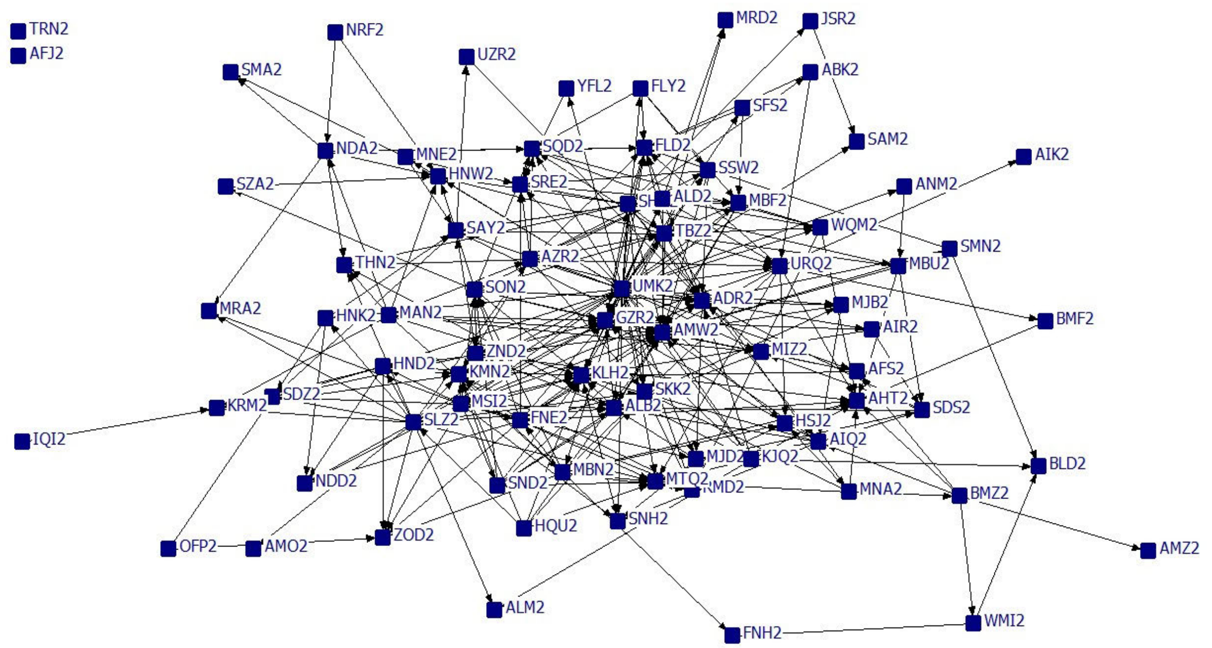
A. HiPos

Fig. 1 represents the sociograms of work and advice network of Zong and Ufone employees. Lines with arrow heads represent the relationship or ties and blue squares represent the employees. For privacy and data confidentiality employees names are coded. There are 708 ties between work and advice network of Zong employees and 859 ties for Ufone employees. As seen from the direction of arrowheads in the below mentioned Fig.1 the network is asymmetric, network ties are not always reciprocated.

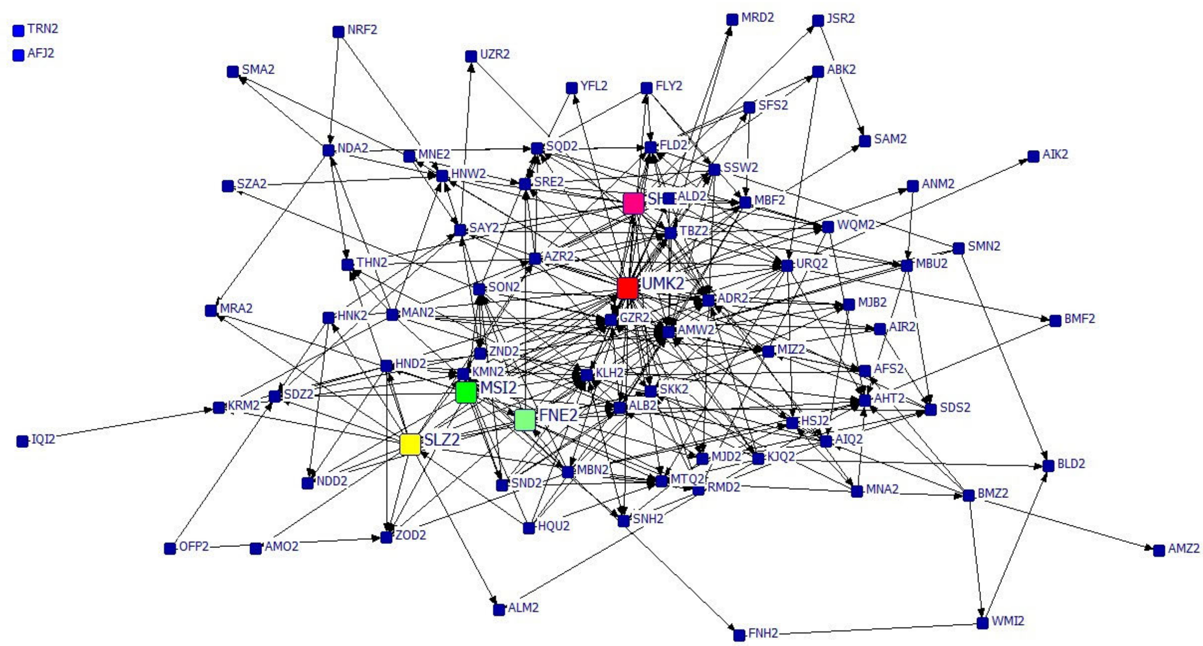
In Fig. 2 and Fig. 3 advice ties of Ufone and Zong employees outside mandatory workflow is represented. HiPos having higher out-degree centrality are highlighted in unique colors (red, green, yellow, pink) based on varying degree centrality scores where blue squares represent Non-HiPos.-

In Fig. 2 (a) and Fig. 3 (a) advice ties of Zong and Ufone employees outside mandatory workflow is represented. Since HiPos are most efficient individuals and are knowledge seekers, they have higher out-degree centrality then their colleagues in their advice network. To distinguish HiPos on sociograms generated by UCINET, all those employees who scored higher on network centrality then rest of the employees are highlighted in unique colors (red, green, yellow, pink) representing HiPos as shown in Fig 2(b) and Fig. 3 (b). Whereas all remaining employees with lower degree centrality are represented by blue squares. Fig. 2 (c) and Fig. 3 (c) illustrates that when HiPos are removed from their network, the advice network becomes less dense and disconnected creating isolate employees, which strengthens the importance of having HiPos in organizational networks.

Along with visual mapping of HiPos, the network centralities computed from quantitative network analysis are represented in tabular form as well. A list of top 5 vertexes (employees) with highest out-degree centrality is presented

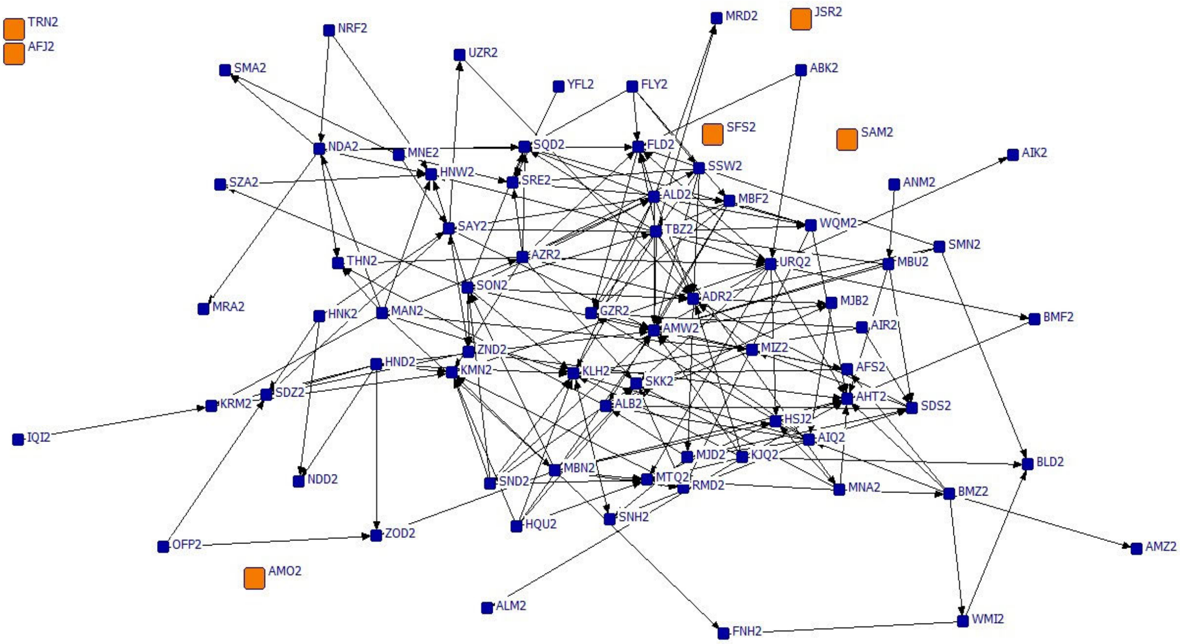


(a) Advice ties outside mandatory workflow



(b) HiPos (red, green, yellow, pink) – Non-HiPos (Blue)

FIGURE 3. Ufone Sociogram of Advice ties outside mandatory workflow.



(c) Sociogram without HiPos

*Isolates (Orange)

FIGURE 3. ***(Continued.)*** **Ufone Sociogram of Advice ties outside mandatory workflow.**

in Table 1 with the total out-going ties and their respective normalized values that represent the vertex's centrality as a fraction of its maximum possible connections. A normalized value of 0.10 means that the vertex holds 10% of all possible connections within the network and 0.51 means that vertex holds 51% of all possible connections.

$$\text{OutDegree Centrality}: \; C_D^{out} = \sum_{j=1}^{n} A_{ij} \tag{4}$$

$$\text{Normalized value}: C'_D\,(i) = \frac{C_D^{out}(i)}{N-1} \tag{5}$$

The network centrality scores of SNA calculated from UCINET for all employees were then imported in SPSS software version 21 for further statistical analysis. To test the strength and direction of correlation between our social network parameters and intention to quit, we performed the Pearson's correlation test. Table 2 shows the mean, standard deviation and bivariate correlations of all variables.

The correlation matrix reveals that there is negative correlation between high potential employees and intention to leave. Since HiPos have higher learning agility and are more motivated, they have higher out-degree centrality in advice network, they go beyond their mandatory work flow network to seek advice on work related matters for their professional development. We hypothesized that when such individuals are able to get the required advice for knowledge and skill outside their work network they feel contented with their work and less compelled to leave their job (H1). A multiple linear regression was calculated to predict turnover intention of HiPos. Our regression analysis result support our hypothesis H1 as seen in Table 3 below. In Model 2, significant negative relationship exists between HiPos and intention to turnover (b = -0.261, F(2,139) = 11.248 $p < 0.001$ with an R^2 of 0.491. The results show that out-degree centrality of HiPos is a significant predictor of Intention to turnover.

B. INFLUENCERS

In Fig. 4 and Fig. 5 advice ties of Ufone and Zong employees with mandatory workflow is represented. Influencers having higher in-degree centrality are highlighted in unique colors (red, green, yellow, pink) based on varying degree centrality scores. Whereas there are few individuals who are not connected to the network because of low degree centrality.

In Fig. 4 (a) and Fig. 5(a) advice ties of Zong and Ufone employees with mandatory workflow is represented. Since Influencer employees are approached the most for advice by their colleagues because of their experience, they have higher in-degree centrality in their organizational network. To identify Influencers of Zong and Ufone, employee sociograms generated by NetDraw based on different network centralities are highlighted in unique colors. Red, green, yellow and pink represent Influencer employees with higher in-degree centrality as shown in Fig. 4 (b) and Fig. 5(b) while blue squares represent employees with lower in-degree centrality. Fig. 4(c) and Fig. 5(c) shows that when Influencer employees are removed from their advice network, the network becomes sparse and disconnected creating many isolate employees

TABLE 1. Top 5 Out-Degree Centrality HiPos.

	HiPos (Employee codes)	Out-degree centrality	Normalized Out-degree centrality
Zong	MSE1,ARZ1	7	0.10
	MSD1	8	0.12
	FMR1	12	0.18
	SED1	15	0.23
	AMR1	53	0.81
Ufone	FNE2	13	0.16
	SHG2	16	0.20
	MS12	17	0.21
	SLZ2	18	0.22
	UMK2	40	0.51

*Employee names are coded for data privacy

TABLE 2. Descriptive statistics, inter-correlation matrix.

Constructs	Mean	SD	1	2	3	4
1 .IQ	3.1033	1.15755	-			
2. HiPo	1.627	0.9937	-.245**	-		
3. Influencer	1.592	0.9314	.267**	.056	-	
4. PIED	3.0018	.75354	-.343**	.313**	-.332**	-

**. Correlation is significant at the 0.01 level (2-tailed).

TABLE 3. Multiple regression analysis.

Constructs	Model 1	Model 2
Constant		
High Potential employees	-0.303*** (0.092)	-0.220* (0.096)
Influencer	0.350*** (0.098)	0.256* (0.103)
Perceived Investment in Employee Development		-0.330 (0.134)
Constant	3.038	4.042
R^2	0.491	0.523
Change in R^2	0.139	0.036
F for change in R^2	11.248***	6.043***

Unstandardized B Coefficients and standard error in brackets.
*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).
***. Correlation is significant at the 0.001 level (2-tailed).

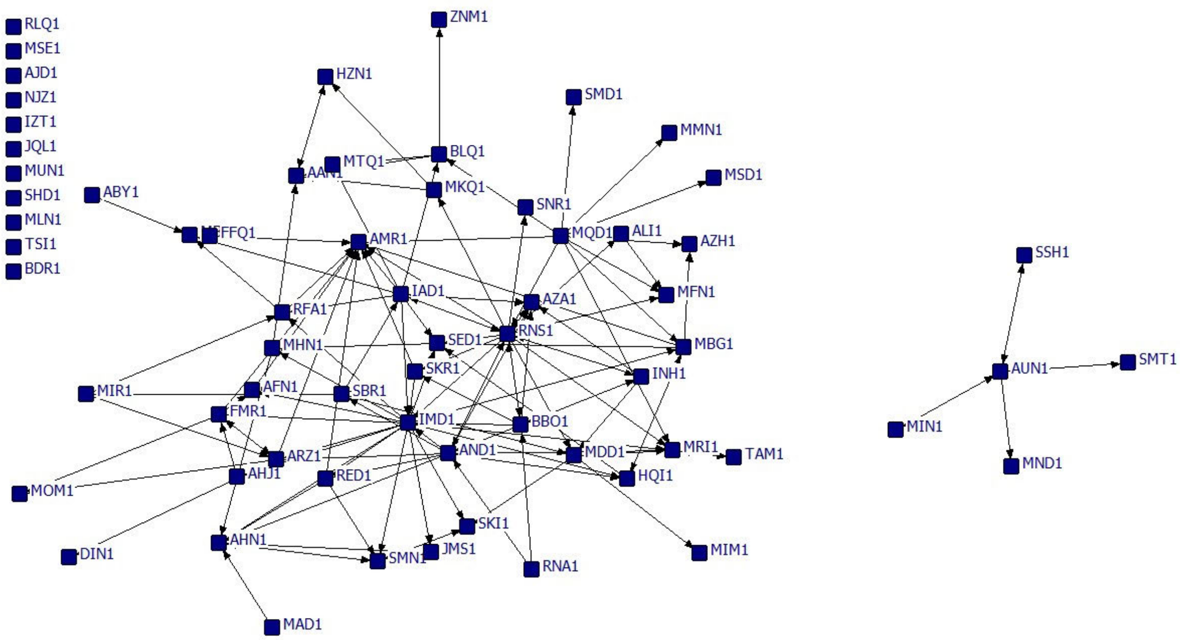
which disrupts the information flow within organization, suggesting the importance of retaining Influencer employees.

The network centralities of individuals identified as Influencers on employee sociograms are listed in tabular form as well. A list of top 5 vertexes (employees) with highest in-degree centrality is presented in Table 4 with the total in-coming ties and their respective normalized values. Employees from Zong and Ufone sharing same in-degree and normalized centrality are also shown in table 4. A normalized value of 0.06 means that the vertex holds 6% and 0.16 mean vertex holds 16% of all possible connections within the network.

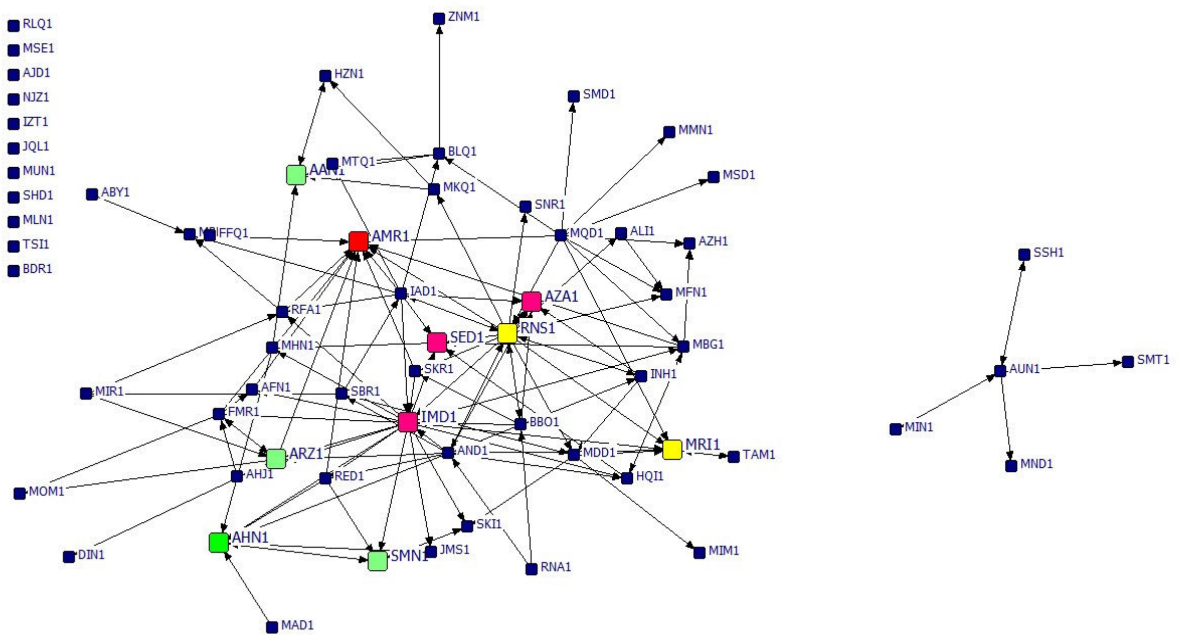
$$\text{InDegree Centrality: } C_D^{in} = \sum_{j=1}^{n} A_{ij} \tag{6}$$

$$\text{Normalized value: } C'_D(i) = \frac{C_D^{in}(i)}{N-1} \tag{7}$$

We hypothesized that higher in-degree centrality of influencers is positively related to intention to turnover H2 (a) in advice network of mandatory workflow. Since influencer employees are considered trustworthy for their expertise, they are approached the most for work related advice by their peers and thus they have higher in-degree centrality as seen in Table 4. A positive correlation between influencers and intention to leave is shown in table 2 of inter correlation matrix supporting our hypothesis. Results of multiple regression analysis of table 3 also validate our hypothesis for model fit. In model 1 of regression table 3, significant relationship exist between influencers and intention to leave with (b = 0.282, p< 0.001 and adjusted $R^2$of 0.157. The regression

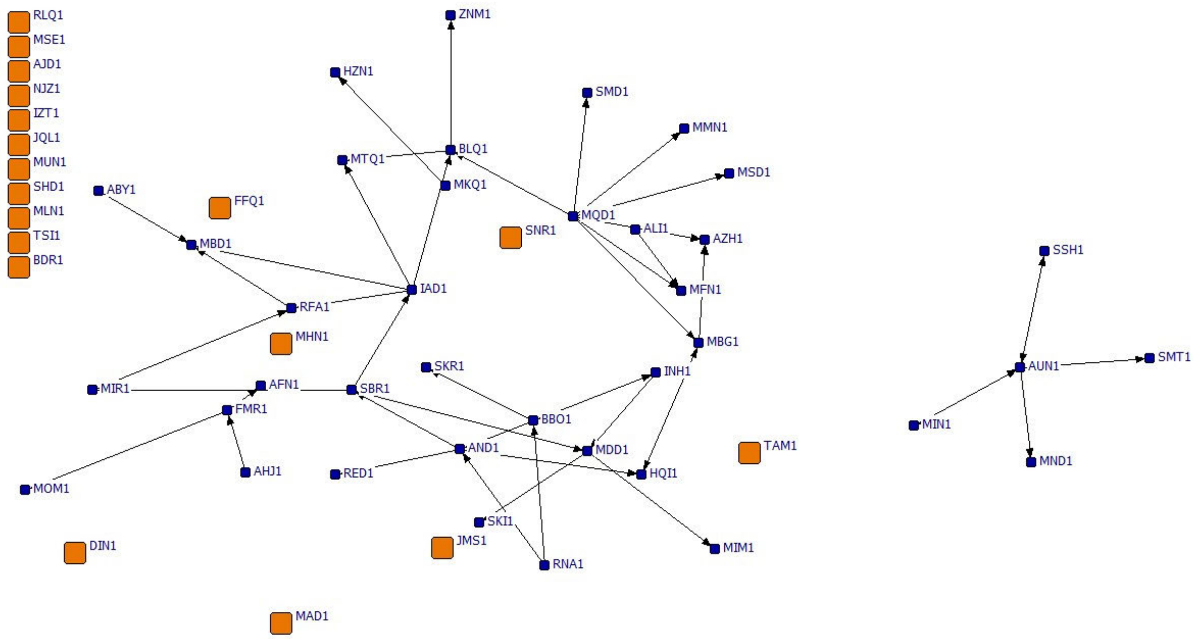


(a) Advice ties with mandatory workflow



(b) Influencers (red, green, yellow, pink) – Non-Influencers (Blue)

FIGURE 4. Zong Sociogram of Advice ties with mandatory workflow.



(c) Sociogram without Influencers-*Isolates (Orange)

FIGURE 4. ***(Continued.)*** **Zong Sociogram of Advice ties with mandatory workflow.**

table shows that 15% of the variance in the intention to leave is predicted by our independent variables.

C. MEDIATING EFFECT OF PERCEIVED INVESTMENT IN EMPLOYEE DEVELOPMENT

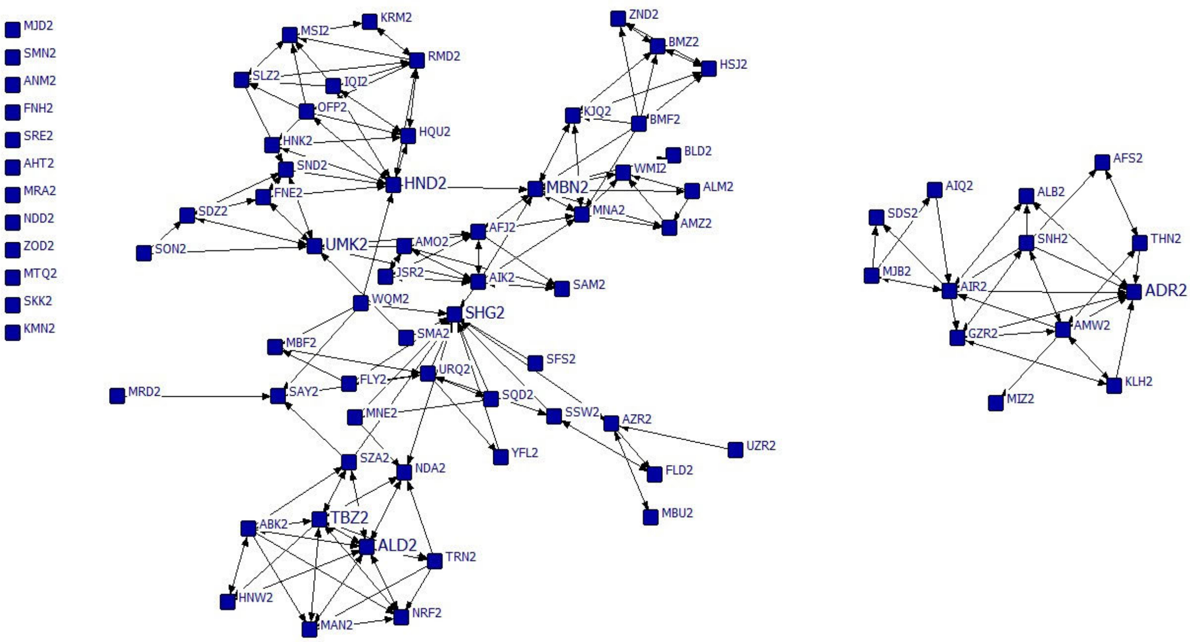
To validate the mediation hypothesis of 2b, we used the percentile boot strapping (5000 permutations) at 95% confidence interval in Process v3.2 [59] of SPSS to estimate the indirect effect of perceived investment in employee development on the relationship between influencer and intention to turnover. Bootstrapping is a random re-sampling of the data to generate more accurate results then sobel test [60].

Fig. 6 shows the mediation results for the relationship between dependent, independent and mediating variable. The path a (direct effect) from influencer and PIED is negative and statistically significant ($b = -0.269$, s.e. $= 0.0645$, $p < 0.001$) indicating that influencers with higher in-degree centrality perceive that their organization does not invest sufficiently in employee development. Path b the direct effect of PIED on intention to turnover is also negative and significant ($b = -0.4383$, s.e. $= 0.1275$, $p < 0.001$) indicating that when an individual feels that perceived investment in employee development is not adequate his intention to leave is higher. Path c' the direct effect of influencer on intention to turnover is positive and significant ($b = 0.2134$, s.e. $= 0.1031$, $p < 0.05$) indicating that influencers with higher in-degree centrality score are more likely to leave then those individuals scoring lower on centrality scores. Path c the total effect of Influencer on intention to turnover is also positive and significant ($b = 0.3313$, s.e. $= 0.1010$, $p < 0.01$).

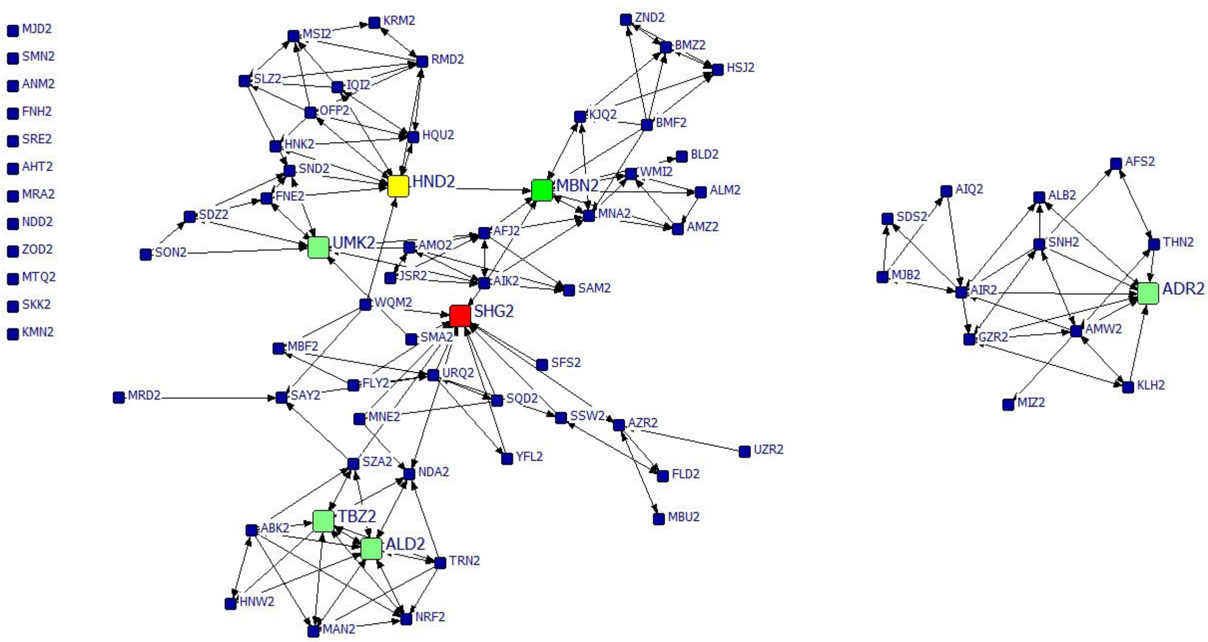
Table 5 shows the effect size, standard error, lower limit confidence interval, upper limit confidence interval and p-values between our variable relationships. The indirect effect of influencer on intention to turnover via PIED is statiscally significant (IE=0.1179) with a 95% confidence interval which did not include zero (0.0406, 0.2004).According to [59], when zero lies outside the upper and lower confidence interval, mediation is established. However our analysis shows that PIED partially mediates the relationship between influencer and intention to turnover since influencer's intention to leave was still significant but to a lesser extent (p value changes from 0.0013 to 0.0404 when PIED is introduced in the model). This indirect effect accounts for 35% on total effect that influencer has on intention to turnover.

V. DISCUSSION

The objective of this research was to apply Social Network Analysis to investigate the multiplex work and advice network of employees in telecom sector to identify the hidden stars and predict their turnover by employing data mining technique. First, we propose to use graph theory for unravelling employee network centrality from their heterogeneous organizational social network. Ucinet and NetDraw was used to identify the star employees (HiPos and Influencers) embedded in the directed adjacency matrix and multiple linear regression was used for predictive analysis. The present study also examined how perceived investment in employee development mediates the relationship between social ties of influencers and their intention to leave and mitigate the

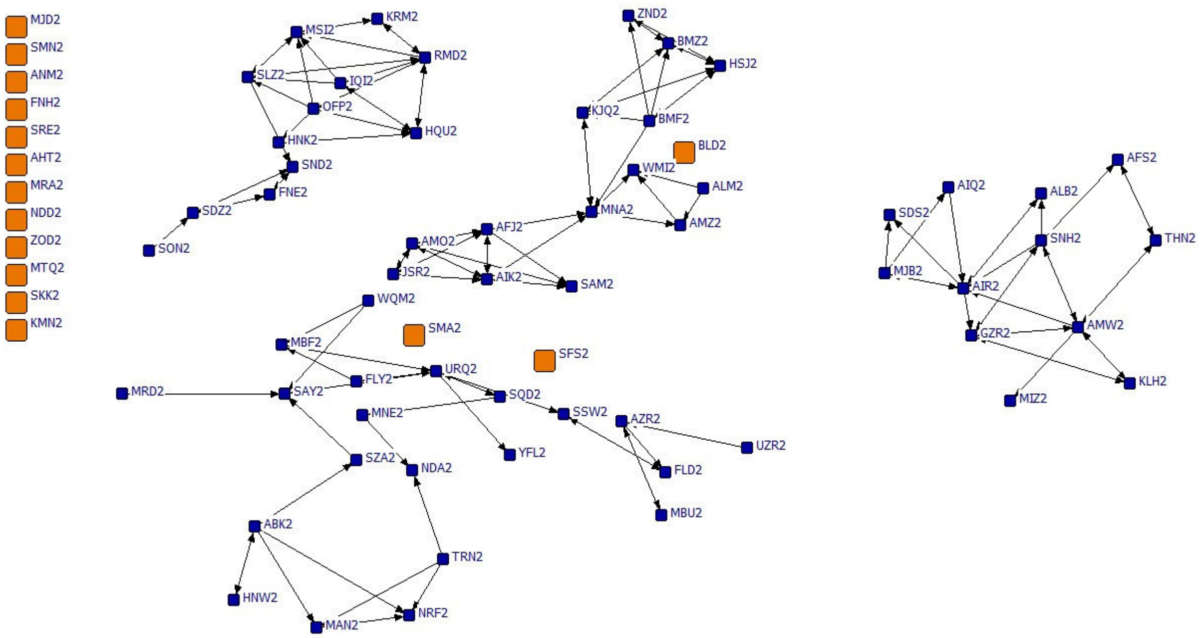


(a) Advice ties with mandatory workflow



(b) Influencers (red, green, yellow, pink) – Non-Influencers (Blue)

FIGURE 5. Ufone Sociogram of Advice ties with mandatory workflow.



(c) Sociogram without Influencers-*Isolates (Orange)

FIGURE 5. ***(Continued.)*** **Ufone Sociogram of Advice ties with mandatory workflow.**

TABLE 4. Top 5 in-degree centrality influencers.

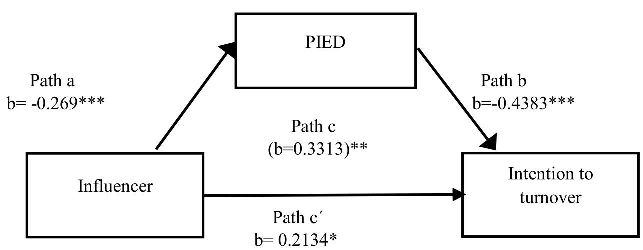
	Influencer (Employee codes)	In-degree centrality	Normalized In-degree centrality
Zong	SMN1,ARZ1,AAN1	4	0.06
	AZA1,SED1,IMD1	5	0.07
	RNS1,MRI1	6	0.09
	AHN1	8	0.12
	AMR1	11	0.16
Ufone	TBZ2,ADR2	7	0.08
	UMK2,ALD2	8	0.10
	HND2	9	0.11
	MBN2	10	0.13
	SHG2	13	0.16

Employee names are coded for data privacy

risk of employee turnover. To the best of our knowledge, this research is the first to conduct Social Network Analysis of HiPos and Influencers and their intention to leave using perceived investment in employee development as a mediator in the context of telecom sector.

The dynamic modelling of employee's workplace social interactions for HiPo and Influencer identification differs from the previous work done by [61] and [35]. They followed a subjective approach for identifying the star employees such as manager's intuitive judgement, employees past performance, gauging social skills and personality assessment. The use of social network analysis to quantitatively recognize the most critical nodes who are the integral part of business success adds to the uniqueness of our research.

Our research results reveal that HiPos with higher out-degree centrality in multiplex work and advice network have negative association with turnover intention, which is consistent with the findings of [62] and [26]. Porter *et al.* [62] found that degree centrality in instrumental (advice) network decreases the likelihood of turnover by taking into account job performance and organizational commitment. Whereas [26] stated that directors with a higher degree cen-



*. Coefficient is significant at the 0.05 level (2-tailed).

**. Coefficient is significant at the 0.01 level (2-tailed).

***. Coefficient is significant at the 0.001 level (2-tailed).

FIGURE 6. Mediation results.

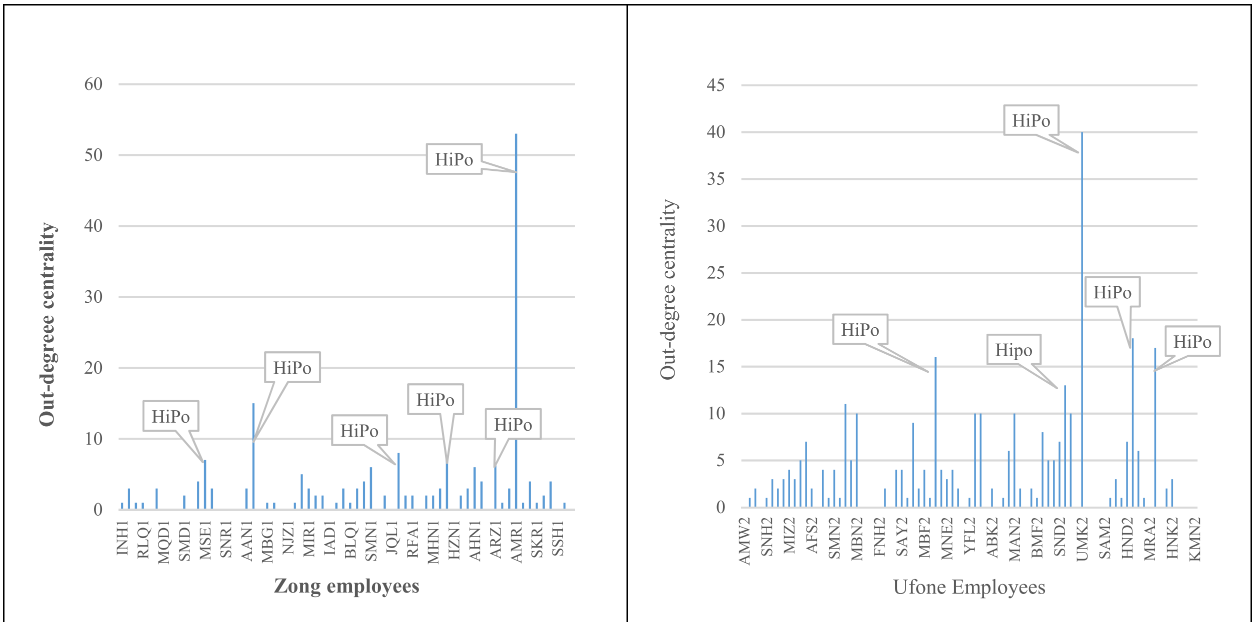
TABLE 5. Mediation analysis result (process 3.2).

Relationships (path)	Effect size	Standard error	LLCI	ULCI	P
Total effect of Influencer on Intention to turnover	0.3313	0.1010	0.1317	0.5309	0.0013
Direct Effect of Influencer on Intention to turnover	0.2134	0.1031	0.0095	0.4174	0.0404
Indirect effect (Bootstrapping) of Influencer on Intention to turnover	0.1179	0.0403	0.0406	0.2004	0 does not lie between Upper and lower CI. p is significant

Number of sampling iterations is equal to 5000

*. Coefficient is significant at the 0.05 level (2-tailed).

**. Coefficient is significant at the 0.01 level (2-tailed).



(a) HiPos in Zong

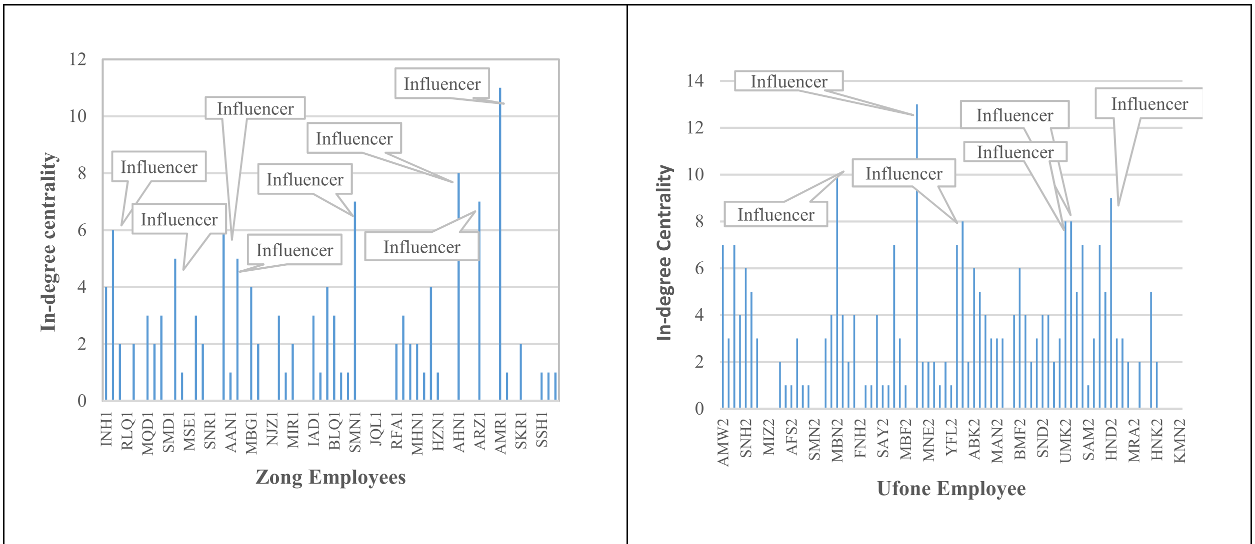
(b) HiPos in Ufone

FIGURE 7. Out-degree centrality of Zong and Ufone employees. HiPos with highest out-degree are highlighted.

trality within the organization have more chances of promotion, they feel more embedded in the system, which in turn reduces their intention to leave.

This research has also strengthened the previous study of [63]. They found that when employees have higher in-degree centrality for advice in mandatory workflow environment, their intention to quit increases if they are not rewarded adequately with distributive justice. However in our study distributive justice had no effect on employee's social interactions and turnover, the reason for this insignificant finding is that reward system in telecom industry is fair and it reflects the efforts put in by the employees.

The above Fig. 7 and Fig 8, shows employee with different degree centrality scores. Employees who scored higher on out-degree are HiPos, whereas those who had higher in-degree are the Influencers. We can see from the graphs that there are only few individuals in Zong and Ufone, who stand out among all the employees because of their higher centrality in their network. These graphs show that the network centrality method employed in this research is very effective and efficient in identifying the star employees embedded in heterogeneous complex networks, who are otherwise invisible to the organizations. Once these employees are identified, organizations can work towards enhancing the retention of



(a) Influencers in Zong

(b) Influencers in Ufone

FIGURE 8. In-degree centrality of Zong and Ufone employees. Influencers with highest in-degree are highlighted.

their key employees by taking preemptive measure before a star falls out.

Whilst other network centralities like Betweenness, Closeness, PageRank and Random Walk method [64]–[67] may be used to identify Influencers and HiPos, where there is a need to only identify the star employees. But our aim of this study was not only identify star employees but also to explore the relationship between degree centrality of these star employees and their turnover intention by modeling the dynamics of their workplace social ties. For this study, considering only degree centrality was sufficient to cater our research need for two reasons.

First for HiPos, we theorized that since HiPos have higher learning agility and are more motivated then others, they have higher out-degree centrality in advice network, they go beyond their mandatory work flow network to seek advice on work related matters for their professional development. A higher out-degree centrality demonstrates higher learning agility and higher motivation. We hypothesized that when such individuals are able to get the required advice for knowledge and skill outside their work network they feel contented with their work and less compelled to leave their job.

For Influencers, we argued that in a mandatory workflow network, when influencers are frequently approached for advice from their colleagues whose request they cannot turn down because of work requirement, they feel frustrated since they have to stop what they are currently doing and fulfill the mandatory advice request first. A higher in-degree demonstrates frequent advice requests by the colleagues because of trust on focal employee for his expertise. We hypothesized that such individuals have more probability for burnout and can have higher turnover intention.

Secondly, the HiPos and Influencers identified in our study, not only scored higher on degree centrality (out-degree for HiPos and in-degree for Influencer) but they also have higher betweenness centrality (results not mentioned in this study but can be provided), which proves that these employees are no doubt star employees of their organizations. On the contrary, there are many nodes which have higher betweenness centrality but these nodes score lower on degree centrality which does not fulfill our research criteria. For these reasons, considering only in-degree and out-degree was sufficient for this research.

Another finding which is not the main focus of our research is that perceived investment in employee development (PIED) is negatively related to turnover intention and it partially mediates the relationship between influencer's in-degree centrality and turnover. This result supports the social exchange theory (SET) that when employees are provided with opportunities for obtaining new skills and competencies, they feel their contributions are valued and their motivation increases. Consequently the employees reciprocate by a decreased turnover intention.

Overall, this research investigated 3 proposed hypothesis, and the results of our study also validates them. The findings enhance our insight of the actual inner working of the white space of the organizations apart from the formal organizational hierarchical structure using relational construct of SNA. Our results indicate that network structure of employees can play a pivotal role for organizational endeavors focusing on retention strategies by investing in core employees who are most at risk of turnover.

VI. CONCLUSION

In this study, we formulated a network centrality based quantitative method to identify the HiPos and Influencers by modeling the dynamics of their workplace social networks using graph theory and visual mapping. We conceptualized our research based on the principle that HiPo individuals have higher learning orientation, they are more competent and tend to develop more social contacts whereas Influencer individuals are most prominent in their social network, approached the most by their peers for advice on work related matters because of their sound technical knowledge and affable personality. We hypothesized that HiPos are less compelled to leave their job when they are able to get the required advice for knowledge and skill whereas Influencers feels overburdened when they are required to provide advice in a mandatory workflow network and their intention to leave increases. We validated these hypothesis using network graph theory and data mining approach. The findings of this study reveal that perceived investment in employee development mediates the relationship between social ties of influencers and intention to leave.

The employee's network centrality determined in this research, guides the telecom operators to investigate the influence of central nodes on dynamical processes of its heterogeneous complex networks. Data mining of informal multiplex networks will help the organizations to visualize the hidden robust networks and use this information to support integration effort across different departments. This new perspective will redesign the traditional practice of talent management, such as new hires, employee development, retention and performance management.

A. PRACTICAL IMPLICATIONS

This research contributes in designing an optimal structure for business intelligence by providing critical insights of the invisible network ties. Knowing who your central nodes are, and how they are connected via edges across different departments will help the managerial hierarchy to look beyond the formal information flows to understand how people collaborate to get work done. Telecom operators will benefit from incorporating analysis of social network data at workplace to understand the network dynamics of their significant nodes and edges alongside their organizational goals to identify and adapt where improvements can and should be made to its structure.

Further, this research identifies the central nodes or key players of the telecom industry whose retention is critical for business success using statistical analysis. Most of the existing HiPo and Influencer identification methods are based on employee's past performance and primarily rely on manager's instinct about who are the star performers, but these approaches are subjective [61]; [35]; [7].The benefit of using SNA and advanced data mining technique is that it can quantitatively identify HiPos and Influencers of your organization using analytical algorithm, provide visual mapping of employee interactions and can predict their turnover, which if taken care of can mitigate recruiting and training costs and reduce future productivity loss.

The findings of this research will help the telecom operators to figure out who really drives performance in the organization so that they can timely invest to retain the quality employees before the competitors hire them. This study will also help the organizations to focus more on perceived investment in employee development for their star employees to enhance their skills, ability and knowledge by providing appropriate training sessions. Such development activities will improve employer-employee relationship and minimize turnover.

B. LIMITATIONS AND FUTURE WORK

Although this research has successfully achieved its proposed objectives, however the findings should be considered in light of some methodological limitations. First, this study is focused on telecom sector of Pakistan, a rapidly evolving industry which is quiet unique then rest of the sectors of the economy. However the future researchers can utilize HiPo and Influencer identification method for other service sectors facing similar challenges of rapid technological advancements.

Second, we followed a cross sectional approach for data collection which may have common method bias (CMB) issue. To avoid CMB, future studies should follow up with longitudinal study to test model fitness. Third, the present study has investigated only two types of multiplex networks (work and advice), other workplace social networks like friendship and avoidance may also be explored for future studies. Fourth, this research examined perceived investment in employee development as a mediator, other variables can be tested for mediation and moderation effect to strengthen and extend this model. Furthermore, we utilized in-degree and out-degree centrality measures for HiPo and Influencer identification, other social network measure like PageRank and Eigenvector centrality may also be studied for future work.

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