Proceedings of the Annual General Donald R. Keith Memorial Conference
West Point, New York, USA
April 24, 2025
A Regional Conference of the Society for Industrial and Systems Engineering

Enhancing Medical Readiness by Leveraging Centrality Measures in Military Healthcare Provider Networks

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Abstract: In this paper, the authors analyze the stakeholders within the DoD Healthcare System and investigate how best to enhance the outreach of pharmaceutical companies that contract with the Defense Logistics Agency (DLA) to military healthcare providers (MHCPs) within the Military Health System (MHS). Representing the MHCPs as a social network, the proposed model uses predefined centrality measures and incorporates stakeholder analysis to weigh the importance of a certain centrality measure. The proposed additive model provides DoD decision-makers with an overall centrality score, thus enhancing their ability to make more informed marketing decisions, such as allocating resources. Building on previous work, the primary purpose of this paper is to present decision-makers with a model in a decision framework that uses centrality measures to enhance product outreach in military healthcare provider networks.

Keywords: defense health, social network analysis, centrality measures, pharmaceuticals, product outreach

1. Introduction

Good health is fundamental to military readiness. A ready fighting force is a healthy fighting force. However, an individual's health can be unpredictable and uncontrollable. Healthcare, on the other hand, is much more manageable. Providing healthcare to service members and their families provides them with the opportunity to maintain good health. Increasing healthcare outreach within the military ensures more service members have access to necessary medical treatment, thus enhancing the medical readiness of the force.

Pharmaceuticals are a key component within healthcare in the DoD. In 2023, the DoD spent $4.06 million on pharmaceutical drugs, 11.4% of the total Defense Health Program budget for 2023 (Defense Health Program Fiscal Year (FY) 2024 President's Budget, 2023). Through defense contracts, the corporate pharmaceutical industry plays a critical role in supporting military medical readiness, constantly seeking to meet the needs of service members. Pharmaceutical companies that contract with the DoD aim to develop and produce drugs to prevent infections, maintain force health, and cure disease, ensuring operational readiness and mission effectiveness. The DoD wants pharmaceutical companies to maximize the number of service members they reach with pharmaceutical products in order to enhance the medical readiness of service members. One of the most effective ways for companies to reach patients with a product is by informing military healthcare providers (MHCPs), as they tend to have the trust of the patient and are actively involved in advising and supporting patient treatment decisions.

This paper is a continuation of our previous work, which is to be published in the 2025 Annual IEEE International Systems Conference (Worpel, Cavana, Rollins, Shawarby, & Bahabry, 2025). The particular contributions of this paper are the application to the DoD, the technical model with an example, and an expanded discussion.

1.1 Stakeholder Analysis

Pharmaceutical distribution in the DoD contains stakeholders on both the macro and micro scales. As seen in Figure 1, the key stakeholders within the macroscale are the DoD, the DLA, the Defense Health Agency (DHA), the Military Health System (MHS), and private-sector pharmaceutical companies. Displayed by the dashed arrows in Figure 1, the DLA provides the DHA, MHS, and MHCPs with an efficient way of purchasing low-cost, high-quality medical supplies. Private-sector pharmaceutical companies engage with the DLA through structured contracting processes to supply medical supplies and pharmaceutical products to the DoD (Defense Logistics Agency, n.d.). The DLA states that a private-sector company awarded a contract is responsible for marketing their company and products to the military services to increase sales (Defense Logistics Agency, n.d.).

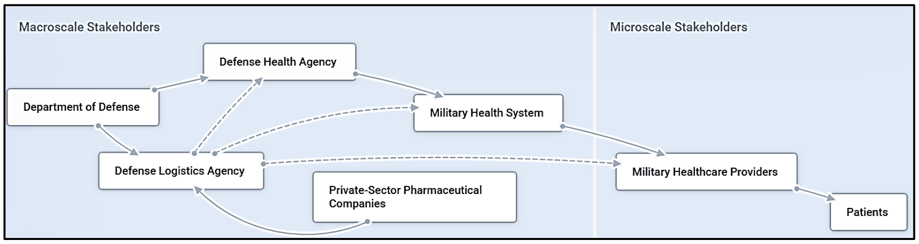

Figure 1. Stakeholder Relationships in DoD Pharmaceutical Distribution

The key stakeholders within the microscale of the DoD pharmaceutical distribution system consist of patients and military healthcare providers (MHCPs). MHCPs primarily include military hospital doctors, military pharmacists, and clinic physicians at other MTFs. They are the primary group authorized to prescribe and administer the product directly to patients. The patients are service members, their dependents, and veterans. As seen in Figure 1, MHCPs are the stakeholders that connect the macro stakeholders to the micro level. By understanding the MHCP network, the DLA and pharmaceutical companies can better enhance their outreach to the prescribers and, thus, to the patients.

1.2 Literature Review

Research has illustrated the effectiveness of utilizing centrality measures in solving real-world problems, such as controlling the COVID-19 virus in 2020. Researchers from the University of Sydney in Australia utilized centrality measures to provide insight into containing the Delta variant of the COVID-19 virus (Uddin, Khan, Lu, Zhou, & Karim, 2022). Focusing on the suburban road networks of Greater Sydney, they found that the degree centrality of the suburban road network was a strong and statistically significant predictor for both COVID-19 vulnerability and severity. At the same time, closeness and eigenvector centrality were statistically significant predictors for COVID-19 vulnerability and severity, respectively (Uddin, Khan, Lu, Zhou, & Karim, 2022).

The current literature on social network analysis in healthcare consistently displays a lack of research on healthcare provider networks. This is evident in reviews like those conducted at the University of Calgary in Canada and the School of Pharmaceutical Sciences at Peking University in Beijing. The researchers from the University of Calgary performed a scoping review of existing literature that uses social network analysis in health research (Grewal, Godley, Wheeler, & Tang, 2024). Focusing particularly on non-communicable diseases, they sought to examine how social network analysis has been used to study the associations between social networks and individual patient health. The review focuses on outcomes at the individual level and does not address professional healthcare provider networks (Grewal, Godley, Wheeler, & Tang, 2024). At Peking University, the researchers collected data from 330 empirical studies to analyze the use of social network analysis in understanding health-professional relationships in different countries (Hu, et al., 2021). Among the studies, they found that 11 successfully utilized social network analysis in mapping communication and collaboration among healthcare providers. The researchers suggest that "understanding and harnessing the power of existing professional networks could facilitate the quality of healthcare delivery and enhance patients' health outcomes" (Hu, et al., 2021).

In addition to there being a lack of research regarding the use of social network analysis with provider networks, there is a noticeable gap in the literature on the integration of social network analysis in military healthcare. Building from the suggestion of the Peking review, we propose that identifying key nodes within military healthcare provider networks can assist pharmaceutical companies that contract with the DLA in improving their product outreach strategy. Enhancing product outreach provides service members with the opportunity for healthcare and, therefore, the opportunity for good health, increasing the overall medical readiness of the force. The primary purpose of this paper is to present decision-makers of DLA contracting pharmaceutical companies with a decision framework that uses centrality measures to enhance product outreach in military healthcare provider networks.

2. Methodology

To develop our model, we considered Social Network Analysis (SNA) and centrality measures with the Additive Value Model. In SNA, social networks model the relationships and connections between individuals, groups, or organizations within a system. Networks consist of nodes representing individuals, groups, or organizations, and edges represent a relationship that exists between nodes. Quantifying relationships in a social network allows us to analyze a node's significance. In social network analysis, centrality measures quantify the characteristics of individual nodes. We focus on four common centrality measures: degree, closeness, betweenness, and eigenvector. Degree centrality measures a node's direct connections, indicating popularity. Closeness centrality reflects a node's closeness in position to other nodes. Betweenness centrality represents the frequency at which a node acts as a bridge between other nodes. Eigenvector centrality factors in the relationships with influential nodes. These measures reflect a node's connection with others and give us insight into the role they play across the network (Gomez, Figueira, & Eusebio, 2012).

Our framework proposes a model that expands on the Additive Value Model (Driscoll, Parnell, & Henderson, 2022). Our model replaces stakeholder value functions with scores derived from centrality measures. The Additive Centrality Model (ACM) quantitatively determines how central a node is in a certain social network by yielding an overall centrality score. The ACM is a summation equation that determines the overall centrality of node i by considering different centrality measures. In our model, we use four common centrality measures. Stakeholders can weigh the centrality measures to allow them to shape the ACM to fit their unique centrality needs. Each centrality measure offers specific insight into a node's role in a network but neglects insights other centrality may offer. The ACM enables stakeholders to determine which centrality measure best applies to the attributes they seek in a node and tailor the ACM to better exploit the network to find nodes with the attributes they desire. As mentioned, our technical model uses four common centrality measures; however, a stakeholder may add or remove additional centrality measures outside of the common four (Worpel, Cavana, Rollins, Shawarby, & Bahabry, 2025).

In the ACM, stakeholders determine weights for each selected centrality measure. Weights are derived to inflate or deflate a centrality's importance in the Overall Centrality Score and are mathematically derived using the Pairwise Comparison Matrix (Saaty, 2008). These weights are normalized and multiplied with their respective centrality measures, creating a weighted centrality measure. These weighted centrality measures are then summed together to output an overall centrality measure for node i. Equation 1 depicts the ACM:

$$C(i) = \sum_{k} w_k * c_k(i), \qquad k \in \{d, c, b, e, \dots\} \tag{1}$$

where i is the node being calculated, $c_k(i)$ is the value of the centrality measure k for node i, w_k is the global weight of the centrality measure k, k is an element of centrality measures, and $C(i)$ is the overall centrality value for node i (Worpel, Cavana, Rollins, Shawarby, & Bahabry, 2025). Stakeholder inputs are captured in two parameters in the ACM: the centrality measures that the function will be an element of ($k \in \{d, c, b, e, \dots\}$) and the global weights (w_k).

3. Technical Model

Our technical model follows Equation 1 to analyze provider connections within a healthcare network and identify the most influential providers based on their centrality score. The input for the technical model is data that reflects interactions or connections between healthcare providers. The model calculates degree, closeness, betweenness, and eigenvector centrality. Then, with the input of stakeholder weights for each centrality measure, the model computes an overall Additive Centrality Score for each provider by summing the weighted scores. The output is a list of the ten most influential providers of the network, ranked by their Additive Centrality Score.

The process for utilizing our technical model has six steps: collecting data, cleaning the data, uploading the dataset, entering the stakeholder weights, running the model, and observing the results. Because of the privacy of military healthcare systems and DoD healthcare data, the data for our example describes non-military provider relationships based on whether they have the same referral capabilities in Medicare and Medicaid (Centers for Medicare & Medicaid Services data). It is important to note that military healthcare providers can be analyzed similarly to these non-military healthcare providers. For this example, one can consider how an MHCP makes referrals just as a non-MHCP makes referrals.

The data must be in a two-column format for the model to run. Column A contains a unique identifier of Provider 1, and Column B contains the unique identifier of a provider that Provider 1 has a connection with, Provider 2. The relationships are duplicated, such as to display Provider 2 in Column A and Provider 1 in Column B, for the model to create an adjacency matrix. With our example data, we cleaned the data so that a provider connection was present if they both shared the ability to refer a patient to hospice care, noted as a "Y" in column HOSPICE. As seen in Figure 2, provider 1760465553 has a connection with provider 1700562584 because they both can refer patients to hospice. The relationship is duplicated in the next row. In the same way, referral capabilities between MHCPs in a military healthcare network would create provider connection data if original DoD healthcare data were accessible.

NPI	PARTB	DME	HHA	PMD	HOSPICE
1558467555	N	Y	N	Y	N
1770667479	N	Y	N	Y	N
1417051921	Y	Y	Y	Y	N
1356025894	Y	Y	Y	Y	N
1972040137	Y	Y	Y	Y	N
1760465553	Y	Y	Y	Y	Y
1295400745	Y	Y	N	N	N
1265446264	Y	Y	N	N	N
1700562584	Y	Y	Y	N	Y
1205257284	Y	Y	N	N	N
1245971480	Y	Y	Y	Y	Y
1164905659	Y	Y	N	N	N
1881384394	Y	Y	Y	Y	N
1255630869	Y	Y	N	N	N
1801093968	Y	Y	Y	Y	Y
1346991064	Y	Y	Y	Y	Y

NPI_1	NPI_2
1760465553	1700562584
1700562584	1760465553
1760465553	1245971480
1245971480	1760465553
1760465553	1801093968
1801093968	1760465553
1760465553	1346991064
1346991064	1760465553

Figure 2. Snippet of Cleaning Data Example

We upload the two-column dataset from Figure 2 to our model and enter stakeholder weights for each centrality measure. The weights we used for this example are in Figure 3. For our example, we considered a scenario where a pharmaceutical company was recently awarded a contract with the DLA and wants to rapidly launch a product to the military services by primarily focusing on degree and eigenvector centrality. The company wants to target MHCPs with a high volume of connections and those with a high volume of connections with highly influential MHCPs. This is just one possible combination of weights out of many, which the company decides based on its situation and priorities.

	vs Degree	*vs Closeness*	*vs Betweeness*	*vs Eigenvector*	**Score**	**Weight**
Degree		5	4	1/2	9.5	0.37
Closeness	1/5		2	1/6	2.37	0.09
Betweeness	1/4	1/2		1/5	0.95	0.04
Eigenvector	2	6	5		13	0.50
				Sum	25.82	1

Figure 3. Pairwise Comparison Matrix for Example

One can understand Figure 3 by considering that the company wants to model degree centrality as 5 times as important as closeness, 4 times as important as betweenness, and ½ as important as eigenvector centrality. The other three rows are in the same manner. After running the model, the result is a list of the ranked providers, Figure 4.

Provider	Additive Centrality Score	Degree Centrality	Closeness Centrality	Betweenness Centrality	Eigenvector Centrality
1003492844	0.998540265	1	1	0.970805301	1
1003298993	0.991104799	0.995184187	0.998401312	1	0.985900404
1013038744	0.728731804	0.708806396	0.916500815	0.487975437	0.729201424
1023117421	0.716067747	0.703368836	0.91516249	0.455295947	0.711215216
1013369552	0.712597843	0.692456628	0.912497747	0.407976013	0.717178896
1033401856	0.712348493	0.703368836	0.91516249	0.441772528	0.70512905
1023404928	0.708303661	0.692456628	0.912497747	0.381136001	0.711274533
1023145463	0.702376162	0.686981867	0.911171293	0.372177198	0.704413038
1033299938	0.693533268	0.697918932	0.913828141	0.410418064	0.674715849
1013159037	0.690322678	0.681494592	0.90984876	0.437656308	0.677863759

Figure 4. Model Output (Ranked Provider List) for CMS Example

With these results, the pharmaceutical company can now make marketing decisions to enhance the outreach of its new product. In Figure 4, providers 1003492844 and 1003298993 have the highest Additive Centrality Score by a margin of 0.27 and, therefore, deserve more marketing attention. To target these providers, the company could perhaps decide to increase the number of sales representatives in the area of that provider, increase the number of emails or calls to these providers, and make other strategic marketing decisions. The results of the ACM provide pharmaceutical companies with data to make better-informed decisions.

4. Discussion

As seen with the example of the technical model, the ACM provides pharmaceutical companies with quantitative information to make decisions considering a provider network. In DoD healthcare, the MHCP network behaves as the social network, and the MHCPs behave as the nodes in the network. When viewing MHCPs as nodes in a network, the ACM enables private-sector pharmaceutical companies that contract with the DLA to identify which MHCPs in the military healthcare network have a high overall centrality score. The companies can then leverage the ACM score to make informed decisions to enhance their product outreach and provide pharmaceutical products to military service members quickly and efficiently.

One significant opportunity our model provides is the ability to optimize the allocation of resources for sales representatives in the pharmaceutical companies that contract with the DoD. Instead of distributing resources evenly based on outdated metrics, pharmaceutical companies can leverage centrality measures to prioritize their efforts based on data and mathematics, directing sales teams to engage with high-value MHCPs. Prioritizing outreach to central nodes allows pharmaceutical companies to maximize outreach while allocating the minimum number of resources. This approach reduces wasted efforts, making outreach efforts to MHCPs more cost-effective (Worpel, Cavana, Rollins, Shawarby, & Bahabry, 2025).

Beyond the benefits to the contracting pharmaceutical companies, our technical model can have a broader impact on the military healthcare industry. Improving the efficiency of product dissemination can help ensure that innovative treatments and medications reach military personnel quickly. Furthermore, the technical model promotes a more connected and responsive MHS, where information and resources can flow more effectively across networks (Worpel, Cavana, Rollins, Shawarby, & Bahabry, 2025).

Although this paper focuses on the military healthcare industry, enhancing product outreach and information dissemination is a necessity in many DoD sectors. The ACM offers DoD decision-makers another tool to analyze social networks to make better-informed decisions in environments with ever-changing parameters. The model allows stakeholders to do more with less, driving positive overall net income for any DoD organization (Worpel, Cavana, Rollins, Shawarby, & Bahabry, 2025).

5. Limitations and Conclusion

A significant limitation of our study is the lack of access to DoD medical referral data between MHCPs due to privacy regulations, data sensitivity, and security protocols regarding military healthcare systems. These restrictions exist to protect sensitive patient information, uphold the integrity of military healthcare systems, and ensure national security. Therefore, our model cannot be tested on real-world DoD referral networks. Moreover, we cannot empirically consider how referral systems for military networks inherently work differently than other referral networks due to numerous unique constraints, like rotation and deployment cycles. However, it is important to note that the significance of the results of the ACM example is not related to the results themselves (i.e., which provider was ranked highest in the CMS dataset). The significance is related to the display of the working model, providing an example of how it works and how it would work with DoD healthcare data if it were available.

Although having empirical DoD limitations, the ACM enables DoD decision-makers to pinpoint MHCPs who hold multiple strategic roles within the network by integrating multiple centrality measures into a composite centrality score. Additionally, stakeholder analysis ensures that the weighting of each centrality measure aligns with the priorities and objectives of DoD decision-makers. This approach allows the DLA and contracting pharmaceutical companies to allocate pharmaceutical resources more effectively, targeting providers who can maximize the impact of medical outreach. By implementing this data-driven model, the DoD can enhance pharmaceutical distribution, improve resource allocation efficiency, and ultimately increase access to critical medications for service members and their families. The ACM empowers the decision-makers in a pharmaceutical company to make more informed, strategic choices to reach service members with a product and enhance the medical readiness of the force.

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