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ORIGINAL PAPER

Mapping the landscape of gynecological cancer – analyzing presenting features by social network analysis

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ABSTRACT

Introduction and aim. The term 'gynecological cancers' refers to a wide range of malignancies that affect the female reproductive system. These types of cancer include ovarian, cervical, uterine, vaginal, and vulvar cancers. This study aims to employ SNA techniques to map the landscape of gynecological cancer by systematically analyzing the presenting features associated with different types of gynecological malignancies.

Material and methods. In this study, a total of 60 women diagnosed with gynecological cancer were included. An exploratory study design was used. A pre-tested questionnaire was used which includes basic demographic details, type of cancer and symptoms presented at the time of diagnosis.

Results. Nearly 44% of the women diagnosed with cancer were between the age of 51 to 60 years. Symptoms such as abdominal pain, lumps, mild and moderate symptoms that appeared to be highly connected and influential among the cancer patients. Abdominal pain, lumps, abdominal distension/bloating, and mild symptoms had a stronger connection with all other symptoms among the cancer patients.

Conclusion. Educating patients about the significance of symptoms such as abdominal pain, lumps, and abdominal distension/bloating in the context of ovarian cancer can empower them to seek timely medical attention. Increased awareness of the potential implications of these symptoms may prompt patients to undergo screening and diagnostic tests earlier, leading to improved detection rates and treatment outcomes.

Keywords. gynecological cancer, mapping, network visualization, social network analysis, symptoms

Introduction

Gynecological cancers encompass a diverse group of malignancies affecting the female reproductive system, including ovarian, cervical, uterine, vaginal, and vulvar cancers. These cancers collectively pose a significant burden on global health, contributing to substantial morbidity and mortality among women worldwide.[1] The estimation of cancer burden from the International Agency for Research on Cancer indicated that gynecological cancers accounted for 19% of worldwide cancer cases.[2] Gynecological cancers in India accounted for 30% of the total cancers among women.[3] A study reported in India, based on the cancer registries, indicated a decline in cervical cancer cases and a rise in breast, ovarian, and uterine corpus cancer cases across most of the registries over the full observation period. Four types of cancer, such as breast, cervix, corpus uteri, and ovary, constitute over 50% of all cancers in women.[4] Despite advances in early detection and treatment modalities, knowing the complexity and heterogeneity of gynecological cancers

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is important. Understanding the clinical characteristics associated with gynecological cancers is paramount for timely diagnosis, appropriate treatment allocation, and improved patient outcomes.[5] The characteristics encompass a spectrum of clinical manifestations, including symptoms, risk factors, demographic characteristics, and diagnostic markers, which can vary widely across different cancer types and stages of cancer.[6]

Conventional methods of analyzing presenting features focus primarily on examining individual variables separately, sometimes missing the complex interconnections and interdependencies between them. Researchers have started using innovative methodologies such as social network analysis to study the complex networks of relationships in medical data due to the limitations of standard techniques.

In recent years, the application of social network analysis (SNA) has emerged as a powerful tool in biomedical research for elucidating complex interactions among various elements within a system.[7] Social network analysis offers a powerful framework for investigating the interconnectedness of presenting features in gynecological cancer cases. By conceptualizing the presenting features as nodes and the relationships between them as edges within a network graph, SNA allows researchers to elucidate the underlying patterns, structures, and dynamics of these complex systems. Through quantitative metrics and visualization techniques, social network analysis enables the identification of key features, central nodes, and subgroups that may influence disease presentation, progression, or response to therapy.

Aim

This study aims to employ SNA techniques to map the landscape of gynecological cancer by systematically analyzing the presenting features associated with different types of gynecological malignancies. Through this approach, this study gains deeper insights into the complex etiology and phenotypic heterogeneity of gynecological cancers, ultimately facilitating more accurate diagnosis, risk stratification, and personalized treatment approaches.

Material and methods

In this study, an exploratory study design was used. Primary data were collected from the cancer patients admitted from April 2023 to February 2024 at a private hospital. Participants were selected from the health records and a face-to-face interview was conducted with a semistructured questionnaire, which included demographic details, menstrual history, existing health problems, and symptoms presented during diagnosis. The dataset included information on patients diagnosed with various gynecological cancers, such as ovarian, cervical, uterine, vaginal, and vulvar cancers, along with their presenting features.

Variable selection

We identified a set of presenting features associated with gynecological cancers, encompassing symptoms, risk factors, and demographic characteristics. Variables were selected based on their clinical relevance, previous literature, and expert consultation to ensure a comprehensive representation of gynecological cancer.

Data preparation

Data were collected by using the software Kobo-collect and then extracted in Excel (Microsoft Corporation, Washington, USA). Prior to analysis, the dataset underwent thorough cleaning and preprocessing to address missing values and outliers. The descriptive analysis was performed in SPSS version 22 (IBM, Armonk, NY, USA), and the network analysis was performed with the help of Python (Python Software Foundation, Wilmington, Delaware, USA).

Social network construction

We constructed a network graph where nodes represent presenting features denoted as S1 to S10 (Table 1), and edges represent the relationship between them. The relationship between presenting features was defined based on co-occurrence or mutual information derived from the dataset.

Table 1. Label for nodes

Nodes	Major classification	Symptoms
S1	Abdominal pain	–
S2	Abdominal distension and bloating	–
S3	Mild symptoms	Loss of appetite, weight loss, giddiness, nausea, vomiting, body ache, headache, fever, cold, fatigue, dry cough
S4	Lumps in the organs	Lumps in breast, eyelid, thigh and abdomen
S5	Pain in body parts	Ear pain, throat pain, body pain, thoracic pain, breast pain, nipple pain
S6	Abnormal discharge	Discharge in breast, vaginal discharge
S7	Abnormal bleeding	Bleeding gums, postmenopausal bleeding, abnormal menstrual bleeding, Irregular periods
S8	Blood	Blood in vomiting and stool
S9	Swelling	Swelling in tongue, breast, eyelid, and abdomen
S10	Moderate symptoms	Pleural effusion, burning sensation, skin growth, skin discoloration, pedal edema, inverted nipple, jaundice, reddish spots, difficulty in swallowing, breathlessness, and constipation

Network analysis

Quantitative metrics were calculated to characterize the network structure, including measures of centrality, weighted degree centrality, and connectivity. Visualization techniques, such as the Kamada-Kawai layout, are used to visualize the network structure and to identify the clusters or subgroups of interconnected features.

Table 2. Demographic details of study participants

Variables	Frequency	Percentage
Age		
31–40	5	8%
41–50	19	31%
51–60	27	44%
61–70	9	15%
71–80	1	2%
Marital status		
Married	48	80%
Unmarried	1	1%
Widowed	10	18%
Separated	1	1%
Religion		
Hindu	55	92%
Muslim	4	7%
Christian	1	1%
Family income		
Below 10,000	26	43%
11,000–20,000	26	43%
21,000–30,000	2	3%
31,000–40,000	1	2%
41,000–50,000	4	7%
Above 50,000	1	2%
Education		
Illiterate	21	35%
Primary School	10	17%
Middle school	16	27%
High school	8	13%
Graduate	2	3%
Professional degree	3	5%
Occupational status		
Unskilled worker	13	22%
Semi-skilled worker	1	2%
Skilled worker	0	0
Clerical/shop/farm	2	3%
Semi profession	0	0
Professional	3	5%
No work	41	68%
BMI		
Underweight	6	10%
Normal	27	45%
Overweight	18	30%
Obesity	9	15%
Periods		
Regular	47	78%
Irregular	13	22%
Flow		
Normal	45	75%
Abnormal	15	25%

Ethical considerations

All data handling and analysis have adhered to ethical guidelines and regulations to ensure patient privacy, confidentiality, and data security. Institutional Ethical Clearance (8494/IEC/2023) was obtained from the SRM Institute of Science and Technology, Kattankulathur.

Results

A total of 60 participants were included in the study (Table 2). Forty four percent of the women were between the ages of 51 to 60, followed by 31% between 41 to 50 years. Among the study participants, 80% of them were married, and 18% of them were widowed. Ninety two percent of the women were Hindu. Forty three percent of the study participant family income fell below 10000 rupees. Sixty eight percent of the study participants were not employed, and 22% were unskilled workers. Forty five percent of the study participants had normal weight, and 30% of them were overweight. Among the study participants, nearly 30% of the women had ovarian cancer, followed by breast cancer (27.8%), colon cancer (6.7%), and endometrial cancer (4.4%) (Table 3).

Table 3. Type of cancer

Type of cancer	Frequency	Percent	Type of cancer	Frequency	Percent
Breast cancer	25	27.8	Lung cancer	3	3.3
Cervical cancer	2	2.2	Multiple myeloma	2	2.2
Cholangio cancer	1	1.1	Ovarian cancer	27	30.0
Colon cancer	6	6.7	Pancreatic cancer	2	2.2
Endometrial cancer	4	4.4	Primary peritoneal cancer	4	4.4
Esophagus cancer	2	2.2	Rectal cancer	3	3.3
Eyelid cancer	2	2.2	Stomach cancer	2	2.2
Gall bladder cancer	1	1.1	Tongue cancer	2	2.2
Vulva cancer	1	1.1	Tonsil cancer	1	1.1

Figure 1 illustrates the basic connection between the symptoms of ovarian cancer. Abdominal pain, abdominal distension and bloating, lumps in the organs, mild and moderate symptoms play an important mediating role for participants having gynecological cancer.

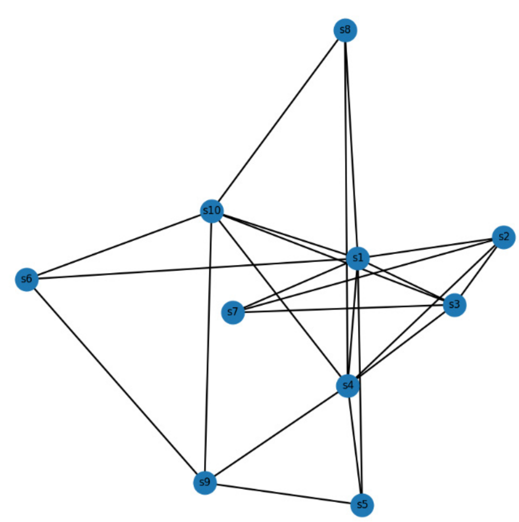

Fig. 1. Connection between the symptoms

Centrality measures

Degree centrality measures the number of edges incident upon a node. Higher values indicate nodes that are more directly connected to other nodes in the graph. Abdominal pain has the highest degree centrality at 0.89, indicating it has the most connections among the other symptoms listed (Table 4).

Table 4. Centrality measures

Nodes	Degree centrality	Betweenness centrality	Closeness centrality	Eigenvector centrality
S1	0.89	0.28	0.9	0.45
S4	0.78	0.15	0.81	0.43
S10	0.67	0.09	0.75	0.38
S3	0.56	0.04	0.69	0.35
S2	0.44	0.01	0.64	0.28
S9	0.44	0.03	0.6	0.24
S5	0.33	0.01	0.6	0.22
S6	0.33	0.01	0.6	0.21
S7	0.33	0.001	0.56	0.21
S8	0.33	0.001	0.6	0.25

Betweenness centrality measures the extent to which a node lies on the shortest paths between other nodes. Higher values suggest nodes that act as bridges between different parts of the network. Abdominal pain has a relatively high betweenness centrality of 0.28, indicating it lies on many shortest paths between other nodes.

Closeness centrality measures how close a node is to all other nodes in the graph. Nodes with higher closeness centrality values are closer to all other nodes in terms of geodesic distance. Abdominal pain has a high closeness centrality of 0.9, indicating it is very close to all other nodes in the graph.

Eigenvector centrality measures the influence of a node in the network, considering both the direct and indirect connections. Nodes with higher eigenvector centrality values are connected to other nodes that are themselves well-connected. In this study abdominal pain and lumps have a relatively high eigenvector centrality of 0.45 and 0.43, indicating it is connected to other nodes that are influential in the network.

Examining all of this data together helps researchers understand the structural significance and impact of each node in the network. Abdominal pain appears to be a highly central node according to all four measures, suggesting it plays a significant role in connecting other nodes and controlling information flow within the network. On the other hand, nodes with lower values across these centrality measures may be less influential or less central in the network structure.

Weighted centrality measures

Table 5 represents weighted degree centrality measures for different symptoms from S1 to S10 in a network, where each symptom is associated with a weighted degree value. Symptoms are the nodes in the network, each representing a symptom observed in the study participants. Weighted degree centrality measures the sum of the weights of the edge's incident upon a node. In other words, it represents the total strength of connections each symptom has with other symptoms in the network. Higher values indicate symptoms that are more strongly connected to other symptoms. Abdominal pain and lumps have the highest weighted degree centrality of 24 each, suggesting that they have the strongest connections with other symptoms in the network, with a total weight of 24. Mild symptoms follow closely with a weighted degree centrality of 21, indicating a strong connection with a total weight of 21. Abdominal distension and bloating have a weighted degree centrality of 21, indicating a moderate level of connection strength with other symptoms. Pain in the organs has a weighted degree centrality of 14, indicating a relatively lower but still significant level of connection strength. Swelling and moderate symptoms have a weighted degree centrality of 10 each, suggesting they have weaker connections compared to the above symptoms. Abnormal discharge and bleeding have a weighted degree centrality of 4, indicating they have even weaker connections. Blood in stools and vomit has the lowest weighted degree centrality of 3, suggesting it has the weakest connections in the network.

Table 5. Weighted degree of the nodes

Symptoms	Weighted degree
S1	24
S4	24
S3	21
S2	16
S5	14
S10	10
S9	10
S6	4
S7	4
S8	3

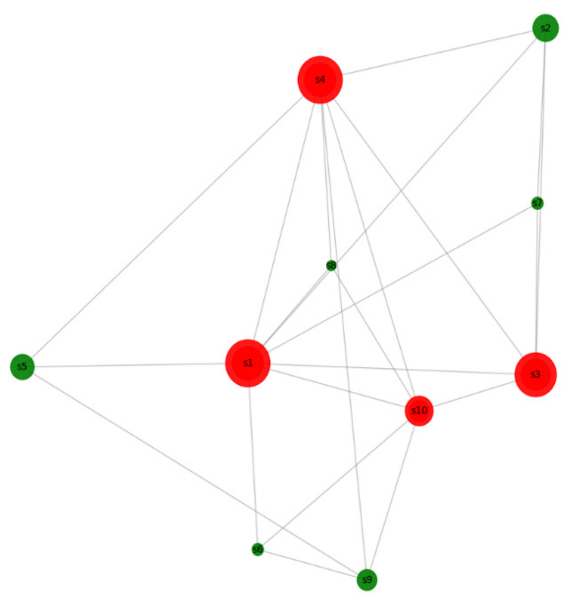

Fig. 2. Network visualization according to the weighted degree centrality

Network visualization with weighted degree centrality

The Kamada-Kawai layout algorithm is a force-directed layout algorithm commonly used for visualizing networks (Fig. 2). It positions the nodes in such a way that nodes with stronger connections are placed closer together, while nodes with weaker or no connections are positioned farther apart.

Node positions: Symptoms such as abdominal pain and lumps that are closer together in the visualization are likely to be more strongly connected in the network. On the contrary, nodes such as discharge, abnormal bleeding, blood in vomit, and stools that are farther apart are likely to have weaker connections or no connections. This arrangement gives an overall network structure and connectivity patterns.

Central nodes: Symptoms such as abdominal pain, lumps, mild and moderate symptoms appear centrally located in the visualization, surrounded by many other nodes, and are likely to be highly connected and influential within the network. These nodes represent key elements or hubs that play significant roles in the network's functioning.

Node community

Symptoms are referred to as nodes, and community refers to the clusters to which each symptom belongs. Nodes within the same community are more densely connected compared to nodes in other communities. Community 0 includes abdominal pain, distension and bloating, mild symptoms, and abnormal bleeding. These nodes are tightly interconnected with each other within the network and form a cohesive subgroup or cluster. They likely share similar characteristics or are involved in similar processes within the network.

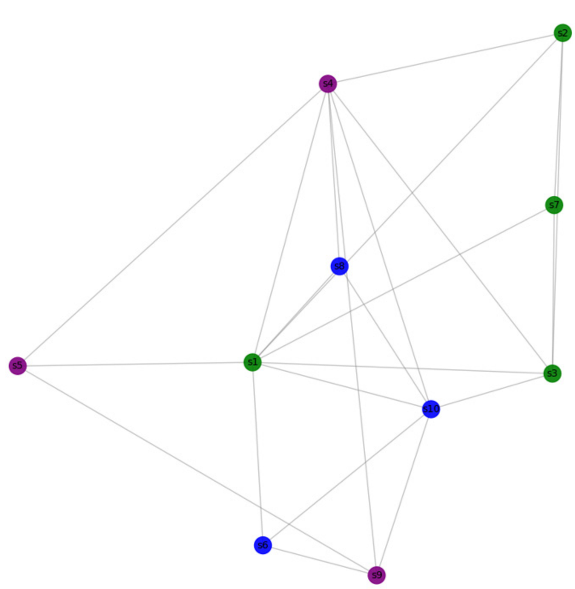

Fig. 3. Network visualization with community coloring

Community 1 includes nodes, lumps, discharge, and blood in vomit and stools. These nodes form another subgroup within the network, distinct from community 0. They are closely connected but less so to the nodes outside their community.

This community 2 includes pain, swelling, and moderate symptoms. These nodes are densely connected but have fewer connections to nodes outside their community.

Network with community coloring

The green color indicates Community 1, the blue color indicates Community 2, and the green color indicates Community 3. These clusters are groups of nodes that are densely connected but have fewer connections to nodes outside the cluster. Identifying these clusters can provide insights into the functional subdivisions within the network (Fig. 3).

Geodesic distance

The shortest path or geodesic distance gives the minimum number of edges between the two nodes in a network (Table 6). Lumps, pain, abnormal discharge, and blood in vomit and stool have the shortest path for abdominal pain.

Table 6. Geodesic distance

Symptoms	Shortest path length from S1
S1	0
S6	1
S8	1
S4	2
S5	2

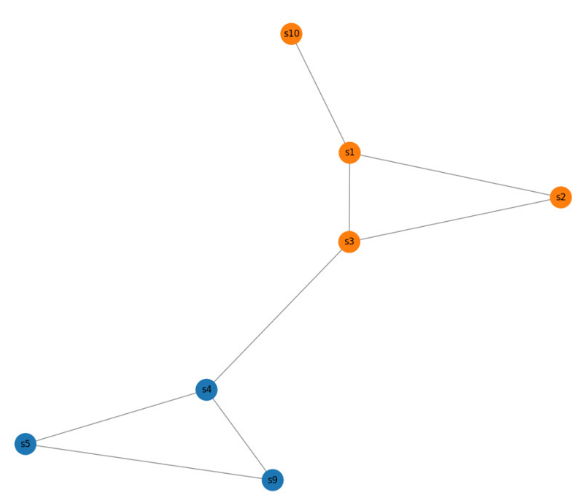

Fig. 4. Sub-network with community coloring

Sub-network weighted degree centrality with community

Using the 50 percentile of weight threshold from the descriptive statistics created a sub-network with edges that have a weight greater than the threshold. Lumps, pain, and swelling form different communities highlighted with blue color. Symptoms within the same community share common attributes or roles within the network.

Abdominal pain, abdominal distension and bloating, and mild and moderate symptoms form different communities highlighted in orange color. Mild symptoms and lump act as the bridge between these two communities (Fig. 4).

Sub-network centrality measures

Sub-network measures the weighted degree centrality of nodes within the subnetwork. The correlation between subnetwork weighted degree centrality and closeness centrality is approximately 0.93, indicating a strong positive correlation between these two measures within the subnetwork. The correlation between closeness centrality and betweenness centrality is approximately 0.93, also indicating a strong positive correlation. The correlation between closeness centrality and betweenness centrality is approximately 0.93, also indicating a strong positive correlation.

Discussion

Abdominal pain appeared to be the most common symptom among the study participants. It also demonstrates significant betweenness centrality, suggesting its importance as a bridge between different parts of the network. Moreover, its high closeness centrality underscores its proximity to all other nodes in the graph. Khan A et al. reported that abdominal pain and abdominal distension were the most common symptoms of ovarian cancer.[8] These results highlight abdominal pain as a crucial indicator and potentially a primary symptom of concern in diagnosing ovarian cancer.

A recent study by Simon et al. reported that 35% of gynecological cancer participants reported frequent symptoms and severe symptoms.[9] Abnormal bleeding in menopausal and post-menopausal women and abnormal uterine bleeding were the most commonly identified symptoms of uterine cancer.[10] These results were similar to the current study. Symptoms such as abdominal pain, abdominal distension and bloating, and mild and moderate symptoms form a cohesive subgroup, indicating potential common pathways or shared underlying mechanisms in cancer manifestation. The network analysis reveals distinct communities within the symptom network, with symptoms clustering together based on their connectivity patterns.

Weighted degree centrality provides insights into the strength of connections between symptoms. Abdominal pain and lumps exhibit the highest weighted degree of centrality, indicating strong connections with other symptoms in the network. The present study suggests that these symptoms are closely intertwined and likely co-occur frequently in patients with ovarian cancer. A study by Ebell et al. reported that abdominal mass, abdominal distension, and abdominal pain were the most common presenting symptoms during the diagnosis of ovarian cancer.[11]

The identification of subnetworks based on weighted degree centrality thresholds further delineates functional subdivisions within the network. The formation of different communities by symptoms like lump, pain, and swelling, as opposed to symptoms like abdominal pain, abdominal distension and bloating, mild, and moderate symptoms, suggests distinct patterns of symptom interactions and potential differences in disease progression or severity. Koo et al. in his study reported that breast lumps (83%) and breast pain (6%) were the frequent symptoms that occurred in breast cancer patients.[12] Another study by Goff et al. reported that back pain (45%) was the most common symptom experienced by the study participants.[13] A study by Bankhead et al. reported that abdominal distension, post-menopausal bleeding, loss of appetite, early satiety, and progressive symptoms were statistically significant variables associated with ovarian cancer.[14] Social network analysis was useful to categorize the symptoms based on their cluster.

The strong positive correlations observed between subnetwork weighted degree centrality and closeness centrality, as well as between closeness centrality and betweenness centrality within the subnetwork, indicate a cohesive structure where highly connected nodes also tend to be centrally located and play significant roles in controlling information flow.

Study limitations and recommendations

This study had a relatively small sample size, which may have limited its findings. Additionally, there is a possibility of recall bias when gathering information on symptom recognition. SNA provides valuable insights into symptom interactions and centrality within the context of gynecological cancer, further research and validation studies are warranted. Continual refinement and validation of symptom networks can enhance our understanding of gynecological cancer pathophysiology, refine diagnostic criteria, and inform the development of targeted therapeutic interventions.

Conclusion

Abdominal pain was identified as the most central symptom in this study, demonstrating its crucial function in interacting with other symptoms. The subnetwork displays a robust positive association among its centrality measurements. Given the central role of abdominal pain in the network and its strong connections with other symptoms, clinicians should prioritize the assessment and evaluation of abdominal pain in patients presenting with potential symptoms of cancer. Rapid and accurate diagnosis of abdominal pain may lead to earlier detection of gynecological cancer and improve patient outcomes. Abdominal pain, lump, abdominal distension/bloating, and moderate symptoms show a strong connection within the network. Clinicians should perform a thorough examination that involves analyzing these symptoms together with abdominal pain to gain a better understanding of the possible existence and development of ovarian cancer. This comprehensive method can improve the accuracy of diagnosis and facilitate timely interventions. Educating women about the significance of symptoms such as abdominal pain, lump, and abdominal distension/bloating in the context of ovarian cancer can empower them to seek timely medical attention. Increased awareness of the potential implications of these symptoms may prompt patients to undergo screening and diagnostic tests earlier, leading to improved detection rates and treatment outcomes.

Declarations

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Author contributions

Conceptualization, I.S. and G.J.; Methodology, G.J.; Software, I.S. and G.J.; Validation, G.J. and I.S.; Formal Analysis, I.S.; Investigation, I.S; Resources, G.J.; Data Curation, I.S. and G.J.; Writing – Original Draft Preparation, I.S.; Writing – Review & Editing, G.J.; Visualization, I.S.; Supervision, G.J.

Conflicts of interest

The authors declare that there is no conflict of interest.

Data availability

Data will not be available online based on ethical considerations. The datasets produced and/or examined in the present study are not accessible to the public owing to the ethical approval requirement that mandates the confidentiality of respondents' answers. On reasonable request, they will be made available by the corresponding author.

Ethics approval

Ethical clearance was obtained from the Institutional Ethics Committee of the SRM Medical College and Research Centre (Approval Number: 8494/IEC/2023).

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