

Threshold Optimization in Constructing Comparative Network Models: A Case Study on Enhancing Laparoscopic Surgical Skill Assessment with Edge Betweenness

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Abstract. Accurate and robust assessment of non-traditional approaches used for training students and professionals in improving laparoscopic surgical skills has been attracting many research studies recently. Such assessment is particularly critical with the recent advances related to virtual environments and AI tools in addressing the need to expand the education and training in the medical domains. Network models and population analysis methods have been identified as excellent approaches in providing the much-needed assessment. This study aims at further advancing the surgical skill assessment by introducing a comparative approach to threshold optimization in analyzing the network models. While the majority of network methods often on arbitrary or hard thresholds for network construction and analysis, this research explores the efficacy of network-based parameters for identifying key elements and clusters in extracting useful information from the constructed networks. We report the positive impact of using network structural parameters, such as edge betweenness and modularity, to conduct robust analysis of the assessment networks. In this work, we employ electromyography (EMG) data and the NASA Task Load Index (NASA-TLX) scores for comprehensive skill evaluation. We present a case study that highlights the advantage of selecting thresholds based on the highest edge betweenness associated with the obtained assessment networks. This proposed approach method proved to be more effective in identifying participants who exhibit significant learning progression, aligning their muscle activation patterns closely with top performers. We demonstrate that optimizing thresholds through edge betweenness offers a more accurate visualization and assessment of skill acquisition in laparoscopic surgery training.

Keywords: Network Models · Threshold Optimization · Training Assessment · Modularity · Edge Betweenness · Clustering Analysis.

1 Introduction

Laparoscopic surgery represents one of the most significant advancements in the medical field, offering patients minimally invasive options with faster recovery times [1, 2]. However, the transition from traditional open surgery to laparoscopic techniques presents a steep learning curve for surgical trainees. The inherent complexity of these procedures, combined with the limited tactile feedback and reliance on two-dimensional video feeds, demands a high degree of cognitive and psychomotor skills [1-3].

The assessment of laparoscopic surgical training effectiveness becomes a major concern, not only for ensuring the competency of future surgeons but also for advancing patient safety and care quality. Traditional methods for evaluating surgical skills, primarily based on direct observation and performance metrics such as task completion time or error rates, have shown limitations in capturing the depth and breadth of a trainee's learning progression [4-6]. These assessments often fail to consider the nuanced interactions between cognitive load, psychomotor abilities, and technical proficiency that define a surgeon's capability. Moreover, the subjective nature of these evaluations can introduce variability and bias, further complicating the assessment process.

Network models have emerged as a powerful tool in surgical education research, providing a novel framework to analyze and visualize the complex interactions between various aspects of surgical performance [7-9]. By constructing networks from data captured during training sessions, such as electromyography (EMG) signals, researchers can visualize and analyze the intricate relationships that exist within the learning environment. Network analysis facilitates the construction of a visual and analytical framework, where nodes (representing individual trainees) and edges (denoting relationships or similarities between them) collectively unveil the dynamics of skill acquisition, knowledge transfer, and performance improvement. By employing network models, this study seeks not merely to evaluate surgical skills in isolation but to understand how these skills evolve, intersect, and amplify within a cohort of learners. This approach is particularly well-suited to address the nuanced demands of laparoscopic surgery training, where the cognitive load, dexterity, and precision play pivotal roles [8, 9]. Through network analysis, we aim to identify meaningful clusters of learners who exhibit similar patterns of skill development or face comparable challenges, thereby offering insights into the effectiveness of training interventions.

However, the effectiveness of network analysis hinges on the selection of appropriate thresholds for defining meaningful connections within the network. The problem, therefore, lies in identifying a method for threshold optimization that accurately reflects the complex dynamics of surgical skill development. Traditional approaches to threshold selection, which often rely on arbitrary or fixed values, may oversimplify the network, omitting critical information or, conversely, clutter the network with irrelevant connections. This study seeks to address this gap by exploring the potential of network-based parameters, such as edge betweenness [10-12] and modularity [12-14], in enhancing the granularity and accuracy of network models for surgical skill assessment. These parameters

offer a more nuanced and data-driven approach to threshold selection, potentially enhancing the visualization and assessment of laparoscopic surgical skills.

By optimizing thresholds based on network properties, researchers can ensure that the resulting models are both robust and sensitive to the subtleties of skill development. This approach not only promises to improve the accuracy and relevance of laparoscopic skill assessments but also contributes to the broader field of surgical education by providing a more sophisticated understanding of how skills are acquired and refined over time. Furthermore, the study explores how the integration of NASA-TLX scores can enrich the network analysis, offering insights into the subjective dimensions of learning and performance in laparoscopic surgery.

2 Methodology

2.1 Needle Passing Task

The needle passing (NP) task is a fundamental component of laparoscopic surgery training, designed to simulate the precision and dexterity required for suturing in a minimally invasive surgical environment [8]. In this task, participants are required to manipulate a virtual needle through a series of designated points (Fig. 1), mimicking the challenges faced during actual surgical procedures. This task was selected for its relevance to core surgical skills and its ability to provide measurable outcomes of psychomotor performance. The study enrolled eighteen participants, ensuring a broad spectrum of experiences by including both medical and non-medical students in equal measure. Criteria for selection included no prior experience with the specific training simulator and no recent injuries that could affect the ability to perform the tasks.



Fig. 1: Needle Passing Task

2.2 EMG Data Collection and Pre-Processing

Data collection centered around the use of electromyography (EMG), a technique that records the electrical activity produced by muscles to quantify muscle effort

and fatigue levels [15]. EMG data were collected using surface electrodes placed on target muscle groups involved in the task, such as the biceps brachii for arm movements and the flexor carpi radialis for wrist actions. This approach allowed for a detailed analysis of the physiological aspects of task performance, providing insights into the muscular demands of laparoscopic procedures.

For the preprocessing of electromyography (EMG) data, we utilized MATLAB due to its advanced signal processing capabilities. The processing of EMG data involved filtering and normalization steps to ensure that measurements could be accurately compared across participants. The signals were band-pass filtered to eliminate noise and then smoothed using a root-mean-square (RMS) technique [16], which provides a measure of the muscle’s electrical activity over time. Normalization was performed against a maximal voluntary contraction (MVC) [17] for each muscle group, allowing for the comparison of muscle activation levels relative to the participant’s maximum capacity. This rigorous data collection and processing methodology facilitated a nuanced understanding of the physical demands of the needle passing task, laying the foundation for subsequent analyses of skill acquisition and progression.

We collected data at three key times: before training started (session-0), after one week of training (session-1), and four weeks after the first training session (session-2). However, we are mainly focusing on the networks formed during the first and second sessions, leaving out the initial baseline session. This decision helps us highlight how participants’ performance changes over time, showing how training affects their laparoscopic surgical skills.

2.3 NASA-TLX Scores

The NASA Task Load Index (NASA-TLX) is a subjective workload assessment tool used to evaluate the perceived workload experienced by individuals while performing tasks [18-20]. The NASA-TLX scores, encompassing dimensions such as mental demand, physical demand, temporal demand, performance, effort, and frustration, offer insights into the subjective experiences of participants as they engage in the needle passing task. The integration of NASA Task Load Index (NASA-TLX) scores into our network model serves to enrich the analysis by providing a subjective measure of workload associated with task performance. By correlating these scores with network properties, we can explore how subjective perceptions of task difficulty and workload relate to objective measures of skill acquisition and learning progression within the network. This holistic approach, combining objective network metrics with subjective workload assessments, provides a more comprehensive framework for understanding the multifaceted nature of surgical skill learning and development.

2.4 Nodes and Edges

In constructing the network for assessing laparoscopic surgical skills, nodes represent the participants who engage in the needle passing task. Each participant

is thus represented as a node in the network, capturing their individual involvement in the skill acquisition process. Edges in the network correspond to the connections between participants, reflecting the relationships inferred from the correlation analysis of EMG data. In our study, the assessment of participants' performance similarities was conducted through Pearson's pairwise correlation coefficient (ρ), which quantifies the linear relationship between the EMG activation patterns of different participants. We have selected Pearson's correlation coefficient (ρ) for our analysis because it is ideally suited for data that adheres to a normal distribution. Pearson's correlation is sensitive to linear relationships between variables, making it a robust choice for quantifying the degree of association between the EMG activation patterns of participants, which were verified to be normally distributed. This statistical method enables a precise measurement of the linear inter-dependencies central to understanding the dynamics of surgical skill development.

This correlation coefficient ranges from 0, indicating no linear correlation, to 1, signaling an exceptionally strong linear relationship between the muscle activation patterns of two participants. Through the computation of (ρ) for every possible pair of participants, we constructed a Correlation Matrix (CM), encapsulating the strength of pairwise linear associations among the participants' EMG data. These correlations are used to establish the connections (edges) between nodes in the network, with stronger correlations yielding more meaningful edges. The resulting network structure encapsulates the interrelationships between participants' performances, offering a holistic view of skill acquisition and progression. To discern substantial correlations indicative of similar performance or learning patterns, we established a correlation threshold, k , as our criterion for similarity. This threshold is pivotal for identifying meaningful connections in the context of surgical skill acquisition, reflecting a deliberate focus on the most substantively similar EMG activation profiles. The decision matrix, henceforth referred to as the Adjacency Matrix (AM) as shown in equation 1, delineates the adjacency matrix for our network graph, based on the following criterion:

$$AM(i, j) = \begin{cases} 1, & \text{if } \rho(P_i, P_j) \geq k \\ 0, & \text{for other cases} \end{cases} \quad (1)$$

where P_i and P_j represent the EMG activation patterns of participants i and j respectively. A value of 1 in $AM[i, j]$ signifies a substantial correlation between the participants i and j , hence establishing a link in the network graph, while a 0 denotes the absence of a link between the nodes. The threshold k for defining significant correlations was determined by a statistical method that considers the distribution of correlation values across all participant pairs. We aimed to establish k at a level that ensures the correlations above it are not only statistically significant but also practically relevant to the skills being assessed. The exact process of calculating k and its role in shaping the network structure is further elaborated in the subsequent section on edge betweenness and modularity for threshold selection, where we discuss how this threshold optimizes the balance between capturing meaningful skill relationships and maintaining

network coherence. This methodological step ensures that our network analysis focuses on the most pertinent relationships, shedding light on the dynamics of skill acquisition among participants engaging in the needle passing task.

2.5 Edge Betweenness and Modularity for Threshold Selection

Edge betweenness, a measure of centrality, identifies the most meaningful connections within the network by quantifying the number of shortest paths passing through an edge (Equation 2) [11]. By selecting a threshold at the point where edge betweenness peaks, we ensure that the network encapsulates the most crucial interactions and learning patterns among participants, thereby preserving the integrity and complexity of the skill acquisition network. This selection criterion is vital for identifying the pivotal connections that facilitate learning progression and skill transfer among trainees.

$$C_b(e) = \sum_{s \neq t} \frac{\sigma_{st}(e)}{\sigma_{st}} \quad (2)$$

where:

- $C_b(e)$ is the edge betweenness centrality of edge e .
- σ_{st} is the total number of shortest paths from node s to node t .
- $\sigma_{st}(e)$ is the number of those paths passing through edge e .
- The sum is calculated over all pairs of nodes (s, t) , where $s \neq t$.

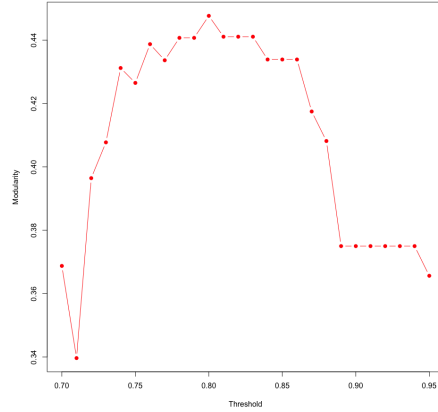
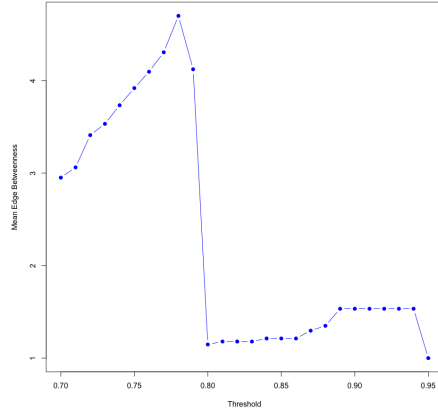
Modularity, on the other hand, assesses the strength of division of a network into modules or communities as shown in equation 3 [12]. High modularity indicates that the network is effectively partitioned into clusters with dense connections internally and fewer connections between clusters. By validating our edge betweenness-based threshold selection with modularity, we ensure that while maintaining crucial learning pathways, the network also accurately reflects distinct groups or communities of skill progression, facilitating a nuanced understanding of how different skills or learning strategies cluster together among participants.

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j) \quad (3)$$

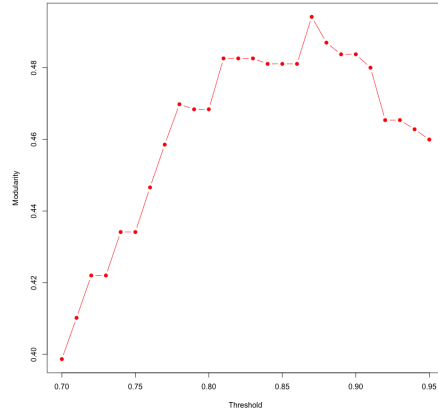
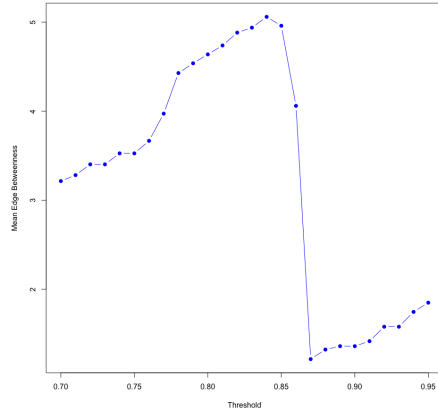
where:

- A_{ij} represents the edge weight between nodes i and j ; for unweighted networks, $A_{ij} = 1$ if there is an edge between i and j , and $A_{ij} = 0$ otherwise.
- k_i and k_j are the sum of the weights of the edges attached to nodes i and j , respectively.
- m is the sum of all edge weights in the network.
- $\delta(c_i, c_j)$ is a delta function that equals 1 if nodes i and j are in the same community, and 0 otherwise.
- The sum runs over all pairs of nodes.

In our study, we plotted the mean edge betweenness of the network at various thresholds (Fig. 2) and selected the threshold where the mean edge betweenness is maximized. Concurrently, we analyzed how modularity varied across these thresholds.



(a) Mean Edge Betweenness Vs Threshold for Networks formed in Session 1 (b) Modularity Vs Threshold for Networks formed in Session 1



(c) Mean Edge Betweenness Vs Threshold for Networks formed in Session 2 (d) Modularity Vs Threshold for Networks formed in Session 2

Fig. 2: Comparative Analysis of Edge Betweenness and Modularity across Different Thresholds for Sessions 1 and 2.

It was observed that at the threshold where modularity reached its maximum, there was a significant decrease in mean edge betweenness. This suggests that

optimizing for maximum modularity alone might not yield the most insightful network structure but instead, selecting a threshold based on peak mean edge betweenness, while ensuring modularity does not significantly deviate from its optimum, offers a more balanced approach.

To elucidate these findings, Fig. 2a represents the mean edge betweenness plotted against various thresholds for networks created in Session 1, providing insights into the optimal threshold selection for this cohort. Similarly, Fig. 2b depicts the modularity plotted against various thresholds for networks developed in Session 1, highlighting the relationship between modularity and network structure at different thresholds. For networks created in Session 2, Fig. 2c illustrates the mean edge betweenness plotted against various thresholds, offering a comparative perspective on the impact of session variability on network properties. Lastly, Fig. 2d represents the modularity plotted against various thresholds for networks created in Session 2, further underlining the nuances of modularity optimization across different sessions. These visual representations substantiate our approach by demonstrating the variability and interplay between mean edge betweenness and modularity across sessions, reinforcing the argument for a balanced threshold selection. This methodological insight underscores the complexity of network analysis, advocating for a strategy that harmonizes both mean edge betweenness and modularity.

3 Results

In the analysis of network models constructed from the electromyography (EMG) data, three distinct thresholds were applied: the commonly utilized hard threshold of 0.70 (Fig. 3a and Fig. 3b), one where the mean edge betweenness was maximized (Fig. 3c and Fig. 3d) and another where modularity was at its highest (Fig. 3e and Fig. 3f). This tripartite-threshold approach facilitated a comparative analysis of network structures and their ability to capture skill progression among participants. Notably, when thresholds were set to maximize mean edge betweenness, the network models yielded significant insights into participant skill improvement, particularly for subjects 4 and 7, who were highlighted in green. This observation suggests that selecting a threshold based on edge betweenness effectively identifies learners who have made notable advancements in their surgical skills.

The color coding of nodes within these networks provided an intuitive and visually compelling representation of participant performance and progression. In our models, nodes representing participants were color-coded based on their performance and improvement over the course of the training sessions. Participants who were identified as superior performers, based on their consistently high levels of skill demonstration across tasks, were color-coded in yellow. This color selection was intended to visually highlight these individuals as benchmarks of excellence within the network, making it easier to identify the core group of participants who have mastered the essential skills required for laparoscopic surgery. In contrast, participants who showed significant improvement in

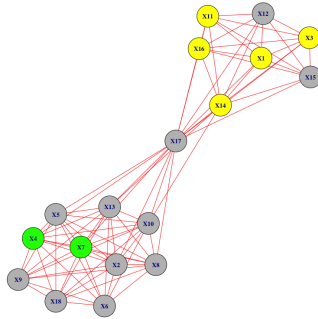
their performance throughout the training period were color-coded in green. The green nodes indicate individuals who, while not initially among the top performers, made notable strides in their skill development, effectively narrowing the gap with the superior performers. This color distinction serves to spotlight the dynamic nature of skill acquisition, showcasing the potential for progress with targeted training and practice. The remaining participants, whose performance did not exhibit substantial improvement or who remained consistent without reaching the level of superior performers, were not highlighted with a specific color. This default representation underscores the variability in learning rates and outcomes among individuals, emphasizing the personalized nature of skill development in laparoscopic surgery.

Moreover, the networks optimized for edge betweenness revealed a compelling structural organization, segregating into two clusters. One of these clusters distinctly grouped the best performers, marked in yellow, alongside subjects 4 and 7, thereby indicating their convergence towards higher skill levels by the end of the training sessions. This emergent clustering phenomenon was less pronounced in networks optimized for modularity, underscoring the advantage of edge betweenness-guided threshold selection in discerning the nuances of skill acquisition and performance improvement. The rest of the subjects, represented in grey, formed the second cluster, suggesting a delineation between those who demonstrated significant improvement and those whose performance remained relatively static or improved at a slower rate.

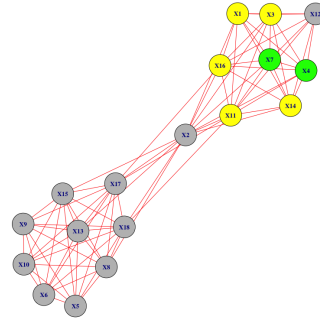
Furthermore, our analysis identified a significant concentration of top performers within the first cluster, distinguished by their higher variability in EMG data. This grouping suggests that the variability observed might be indicative of more effective or advanced learning strategies being employed by these participants. In contrast, the second cluster, characterized by less EMG variability, lacked a significant presence of top performers. This observation implies that while stability in muscle activation patterns can signify proficiency, the dynamic variability in EMG responses among top performers may reflect ongoing optimization and refinement of surgical techniques.

These insights, drawn from the comparative analysis of EMG data and network model clustering, underscore the multifaceted nature of surgical skill development. The presence of distinct clusters, delineated by EMG variability and the concentration of top performers, offers valuable perspectives on the learning trajectories of surgical trainees. It suggests that both the exploration of diverse muscle activation strategies and the stabilization of efficient patterns play critical roles in the acquisition of laparoscopic surgical skills.

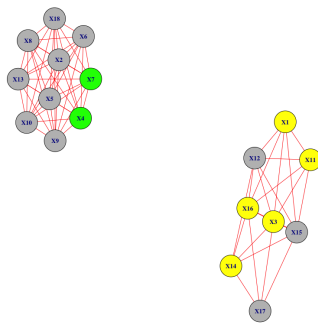
By leveraging the detailed data provided by EMG analysis and the structural insights from network models, this study contributes to a deeper understanding of how surgical trainees progress and differentiate in their skill levels. The observed patterns of EMG variability and performance clustering not only validate the utility of network analysis for surgical education research but also highlight the potential for tailoring training interventions to support diverse learning needs and optimize skill development pathways.



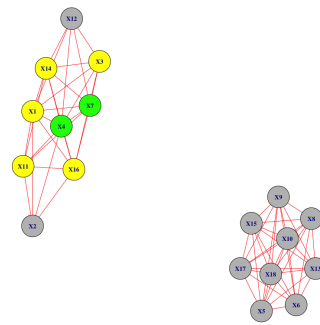
(a) Session 1 Network Model at a Threshold of 0.70



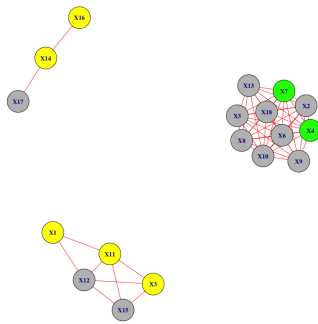
(b) Session 2 Network Model at a Threshold of 0.70



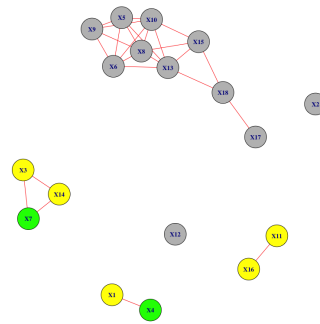
(c) Session 1 Network Model at Highest Edge Betweenness



(d) Session 2 Network Model at Highest Edge Betweenness



(e) Session 1 Network Model at Highest Modularity



(f) Session 2 Network Model at Highest Modularity

Fig. 3: Comparison of network models formed at different thresholds for Session 1 and Session 2. Nodes colored in yellow are the best performers. Nodes colored in green are the participants who have improved their performance moving from session 1 to session 2. The rest of the participant nodes are colored in grey.

These results underscore the utility of network analysis, particularly with thresholds optimized for mean edge betweenness, in surgical education research. By offering a clear visual and quantitative differentiation between varying levels of skill acquisition, the approach enables educators and researchers to pinpoint which participants benefit most from training, potentially guiding more personalized or intensified instructional strategies for those lagging behind. Furthermore, the correlation of network structures with actual performance improvement evidenced by the integration of subjects 4 and 7 into the cluster of top performers validates the method's effectiveness in assessing and understanding the intricate process of learning in surgical training environments.

3.1 Enrichment Analysis

In analyzing the network formations across multiple sessions, we observed meaningful patterns in participants' performance and skill progression, corroborated by subjective assessments through the NASA TLX scores. Initially, participants faced substantial mental and physical demands, reflected in higher scores across these dimensions. However, as the sessions progressed, notable changes emerged, indicating the impact of training and skill acquisition on workload and performance.

Among the participants, those consistently exhibiting superior performance (subjects 1, 3, 11, 14, and 16) demonstrated a remarkable reduction in mental and physical demand scores over time. This decline suggests a more efficient utilization of cognitive and physical resources, indicating enhanced skill acquisition and task familiarity. Concurrently, their performance scores exhibited a steady upward trend, aligning with their improved proficiency in task execution. This pattern of improvement among the high-performing participants suggests that targeted and continuous training can significantly enhance the efficiency of skill acquisition, reducing cognitive and physical strain over time.

Conversely, participants encountering greater challenges with the task (subjects in Grey) maintained relatively higher mental and physical demand scores throughout the sessions. Despite efforts to adapt and improve, these individuals struggled to achieve comparable levels of skill acquisition, as reflected in their performance scores and subjective experiences of effort and frustration.

Moreover, the network formations provided visual representations of these trends, particularly highlighting the clustering of participants based on their performance levels. Notably, after additional training, subjects 4 and 7 demonstrated notable improvements, evident from their inclusion within the cluster of best performers. This observation aligns with the NASA TLX scores, indicating reduced mental and physical demands, alongside enhanced performance and decreased feelings of effort and frustration.

Overall, the integration of subjective assessments through NASA TLX scores provided valuable insights into the nuanced dynamics of skill acquisition and performance progression. These findings underscore the importance of considering both objective performance metrics and subjective experiences in evaluating

surgical training outcomes, paving the way for more comprehensive and tailored approaches to skill development in laparoscopic surgery.

4 Discussion

The selection of an appropriate threshold for constructing network models from electromyography (EMG) data significantly influences the interpretation and assessment of surgical skill development. Traditional methods of applying hard thresholds, although simple and straightforward, often fail to account for the complexity and variability inherent to the process of acquiring surgical skills. This study underscores the importance of selecting an optimal threshold to accurately identify subtle patterns of skill acquisition and progression among participants. Utilizing a threshold that is excessively high risks ignoring crucial yet weaker correlations, while a threshold that is too low may introduce irrelevant connections into the network, obscuring significant patterns of improvement.

Optimizing threshold selection through edge betweenness offers several advantages. Firstly, it enhances the sensitivity of detecting performance changes over time, enabling the identification of participants who demonstrate significant advancements in their skills. This method's adaptability is particularly beneficial in the dynamic context of learning and skill acquisition, as it can accommodate a wide range of correlation strengths and complexities within the network. Moreover, by concentrating on the most impactful interactions, edge betweenness optimization ensures a focused analysis on the relationships that most accurately reflect skill progression, thereby improving the overall accuracy and relevance of assessments.

Analysis of the EMG data revealed that the superior performers (yellow nodes) and those who improved significantly (green nodes) displayed distinct patterns of muscle activation. Specifically, one group exhibited more variability in EMG muscle values, suggesting a more dynamic and adaptive approach to task execution, while the other group showed less variability, indicating a possibly more consistent but less flexible technique. These findings, visualized through the network models and the color-coded nodes, offer valuable insights into the multifaceted nature of skill acquisition in laparoscopic surgery. By correlating EMG data patterns with performance levels and improvements, our study highlights the potential of using network analysis and physiological data to inform and enhance surgical training methodologies.

The incorporation of subjective workload assessments, such as the NASA Task Load Index (NASA-TLX), alongside network model analyses introduces a more comprehensive approach to evaluating surgical training. This combination acknowledges that acquiring surgical skills is not purely a physical endeavor but also encompasses cognitive, psychological, and emotional facets. Incorporating subjective workload measures provides a holistic evaluation of a trainee's experience, integrating both physical performance and cognitive aspects of surgical skills learning. Such a dual approach enables the provision of more personalized feedback and training interventions, enhancing the effectiveness of training

programs. Furthermore, understanding the interplay between subjective workload and performance offers insights into how stress and cognitive load affect skill development, which is crucial for designing optimized training environments and protocols. This comprehensive understanding of skill acquisition, grounded in both objective and subjective assessments, paves the way for more effective training methodologies and improved surgical education outcomes.

Beyond the confines of laparoscopic surgery and even the broader medical field, investigating the applicability of our methodology across various disciplines could uncover its potential to revolutionize professional training and skill assessment on a much wider scale. Furthermore, integrating this innovative approach with simulation-based training technologies could open new frontiers in surgical education. This integration promises to facilitate real-time feedback and adjustments, significantly enhancing the training process by providing trainees with immediate insights into their performance and areas for improvement.

5 Conclusion

With the emergence of various models for training and education, innovative assessment models need to be developed. This is particularly critical in domains where there is shortage of workforce and where assessment is essential before adopting new training practices. This is certainly the case for the medical domain, especially for training medical students and professionals to master surgical skills. This study introduced a novel methodology for further advancing how network models and population analysis can be used for the assessment of surgical skills training. We showed that the quality and robustness of using network-based approaches for assessment can be enhanced by how thresholds are selected in the clustering analysis of the constructed networks. We propose the use of soft thresholds based on well-defined network parameters such as modularity and edge betweenness in assessing the performance of trainees during training sessions of skill acquisition in laparoscopic surgery. By integrating electromyography (EMG) data with subjective workload assessments, we developed a comprehensive framework that offers a deeper insight into the complex dynamics of surgical skill development. Our findings highlight the value in using network models for the assessment process and the significance of conducting the associated clustering analysis using optimizing threshold selection based on edge betweenness.

We introduce an advanced analytical framework that not only surpasses conventional evaluation methods but also supports the development of personalized training programs. These programs can be tailored based on individual progress and specific needs identified through the network analysis, thereby enhancing the effectiveness of surgical training. Furthermore, by combining EMG data with NASA-TLX scores, our study underscores the importance of considering both physiological and psychological factors in the training assessment. This holistic approach paves the way for more precise and effective training methodologies in laparoscopic surgery.

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