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Topological Network Analysis and its Application on Revealing Dimensions of Student Satisfaction Under the COVID-19 Pandemic

Mansooreh Kazemilari¹0, Dalia Streimikiene²0

ABSTRACT

Topological network analysis is an advanced tool for revealing customer satisfaction in marketing research and other fields. The university sector plays a vital and competitive role in contributing to a country's development. Students are regarded not only as a source of income but also as a key criterion for attaining the vision and mission of reaching international standards for universities. Student satisfaction is characterized as a comprehensive assessment of the educational experience, formed by comparing initial expectations with the perceived performance following the completion of the educational cycle. The assessment of students' satisfaction is a continuous process that demands ongoing monitoring to maintain high ranks of quality. Because of the disturbance caused by the COVID-19 pandemic, academic institutions adjusted their curricula and delivery methods to align with the emerging norms of online learning. Assessing student satisfaction is critical for determining how effective the online teaching method is. To understand the key factors influencing student satisfaction, the study examines the interconnections among three dimensions (24 items) by using correlation network analysis and Minimal Spanning Tree (MST) methods. Dioid algebra simplifies the MST search into a single step by constructing a converging sequence, eliminating the need for convergence verification, and centrality measures are employed to interpret and present the network results. The findings suggest a more precise conclusion: To enhance student satisfaction, it is imperative to allocate greater focus towards refining teaching methodologies, enhancing the pandemic study program, and improving the course content for online education.

KEY WORDS: topological network analysis, dioid algebra, student satisfaction, online learning.

JEL Classification: 123, C55, 112, D85.

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1. Introduction

Economic advancement can lead to an increase in educational trade, as countries have demonstrated the crucial role of education in accelerating economic growth. The progress of development impacts the growing interest in education.

The desire for advanced education is expected to persist, and governments embrace educational

trade with the goal of offering superior quality education and a more extensive range of study options (Quispe-Prieto et al., 2021).

According to Ng and Forbes (2009), it is evident that regardless of universities' perceptions of students' desires, students are the consumers of advanced education, and their contentment with the university experience holds significant importance. In today's highly competitive landscape of interna-

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tional education, grasping the elements that impact student satisfaction could enable educational institutions and governmental bodies to enhance and evolve their offerings. This improvement aims to better meet the needs of prospective students, ultimately attracting a larger student population (Songsathaphorn et al., 2014).

Due to the emergence of the COVID-19 pandemic, there has been a significant transformation in the education system, experiencing a pronounced shift from traditional on-campus instruction to virtual teaching facilitated by online learning and digital technologies. This unexpected change has presented numerous challenges for students, teachers, and academic institutions. A key challenge is the implementation of online education systems of superior quality, incorporating the latest technologies in online learning, and ensuring the delivery of high-caliber education (Butt et al., 2022; Kornpitack & Sawmong, 2022; Mohd Satar et al., 2020).

Despite the inevitability of e-learning becoming the new norm in educational institutions, the abrupt transition raises concerns about the quality of delivery, infrastructure preparedness, and the adequacy of training (Mohd Satar et al., 2020). While many studies have examined different facets of e-learning satisfaction, it is essential to validate these theories in the context of the e-learning experience during crises. Additionally, there is a need to explore the success factors for implementing elearning in such situations, considering the existing theoretical frameworks (Butt, Mahmood, & Saleem, 2022).

Cortés, et al. (2019) assert that the student should not be perceived merely as a client or a passive recipient of services. According to their perspective, conducting research on student satisfaction is a meaningful contribution to enhancing the overall quality of educational services. This approach emphasizes the need for ongoing improvements in educational services. Therefore, it is essential to actively seek feedback from students regarding their satisfaction with the educational institution's quality and competitive standards (Sánchez Quintero, 2018; Quispe-Prieto et al., 2021;).

The university must assess the dimensions of students' satisfaction and the factors affecting it. The present research is the first one that considers the dimensions of students' satisfaction in online learning by using the application of algebraic structure in a correlation network-based approach as a theoretical basis to analyse factors' behaviour.

The primary aims of this study are: (a) to pinpoint factors that positively impact student satisfaction during the COVID-19 pandemic, (b) to assess students' satisfaction with online education, and (c) to offer recommendations for both universities and government stakeholders.

This quantitative study employs a satisfaction survey as its primary method for data collection, focusing on evaluating the factors influencing the satisfaction of students at Shiraz University in Iran. A topological analysis method is employed to assist in interpreting the existing relationships among all factors and identifying the influential factors contributing to students' satisfaction.

2. Literature Review

2.1. Previous Research on Students' Satisfaction During the COVID-19

The quality of service at the university benefits from students' input regarding teaching methods, learning environment, interaction, and their motivation to study. These aspects, whether internal or external, play a significant role in shaping an individual's academic satisfaction (Merino-Soto, 2017).

Rosario Rodríguez et al. (2020) introduce a practical model for evaluating satisfaction using a cross-sectional, non-experimental, exploratory, and descriptive design. Their research, involving 167 students from 17 universities in Puerto Rico, offers valuable insights into methodologies for assessing satisfaction (Rosario-Rodríguez et al., 2020).

Mohd Satar et al. (2020) investigated how IT characteristics influence students' satisfaction with online learning during the lockdown period of the COVID-19 pandemic. They conducted an online survey in Malaysia, gathering data from a sample of 470 students selected through convenience sampling, as universities transitioned their classes to virtual modality (Mohd Satar et al., 2020).

Quispe-Prieto et al. (2021) employed systems concepts in their investigation to explore students' experiences and satisfaction with the online learning platform from the viewpoint of students within the sample of three higher education institutions in their study.

These studies pave the way for examining abrupt shifts in educational modality, specifically the transition from traditional classroom to online approaches, and their effects on students, as highlighted by Rosario-Rodríguez et al. (2020).

After reviewing the literature and in line with the study by Quispe-Prieto et al. (2021), it was found that student satisfaction is linked to three main dimensions: (a) satisfaction with support and adaptation in online environments, (b) satisfaction with interaction in online classrooms, and (c) satisfaction with the progression of the academic program (Quispe-Prieto et al., 2021).

2.2. Algebraic Structure of Dioid Algebra

Classical algebraic structures like groups, rings, and fields have been foundational to the majority of advancements in Mathematics and Physics over the past three to four centuries. However, the scope of mathematical models has significantly expanded due to the emergence of new approaches like Fuzzy Set theory and the increasing need for problem-solving techniques in graphs and Operations Research applications (Gondran & Minoux, 2008). Over the last three to four decades, different algebraic structures like semirings and dioids have been thoroughly investigated and have become significant tools and models pertaining to fuzzy sets and their uses for addressing a wide range of non-classical problems in areas such as mathematical physics, decision analysis, operations research, fuzzy set theory, and automatic control (Gondran & Minoux, 2007). Many research works explicitly mention the semiring structure, where the canonical order property is present in almost all instances, canonical order property almost always present, often due to the idempotency of \oplus . Consequently, many algebraic findings in the literature on Fuzzy Sets can be understood as properties of dioids (Gondrana & Minoux, 2007).

A significant example is the elementary fuzzy

algebra ([0,1], max, min), which bears a close relationship to the algebraic structure (\mathbb{R} , max, min). This structure has been referred to by various names in the literature, including 'Minimax Algebra' (Gavalec, 2002), 'Bottleneck Algebra' (Cechlárová, 2003), 'Fuzzy Algebra' (Cechlárová, 1995), and 'MV-Algebra' (Kroupa, 2006).

Primary sources for semirings include Hebisch and Weinert (1998) and Golan (1999, 2013). Gondran and Minoux began a thorough examination of dioids, a subset of semirings distinguished by their canonical ordering in relation to addition, with initial research in 1978 and 1984, followed by further developments in 2001. In an arbitrary semiring (D, \oplus , \otimes), the set D is defined with two operations: "addition" (\oplus) and "multiplication" (\otimes), both of which are closed operations. The standard notation is $\mathbb{D} = (D, \oplus, \otimes)$, where for $a, b \in \mathbb{R}^+$, we define $a \oplus b = \min \{a, b\}$ and $a \otimes b = \max \{a, b\}$. As such, (D, \oplus , \otimes) takes on the structure of a canonically ordered semiring, referred to as a dioid.

In broader terms, it should be noted that the max and min operations, which provide the set of reals with the structure of a canonically ordered monoid, naturally emerge in many algebraic models, leading to numerous applications of dioid structures. In some notable instances involving different types of dioids, (\mathbb{R} , min, +) and (\mathbb{R} , max, min) are used as natural frameworks for addressing the maximum or minimum capacity path problem, which is closely linked to the maximum/minimum weight spanning tree problem (Gondran, 1975, Pan & Leif, 1989).

In this paper, we thoroughly investigate the application of algebraic structures in the minimum weight spanning tree. By defining dioid algebra, we standardize minimum spanning tree problems based on distance matrices and apply them to the network of student satisfaction dimensions. This approach integrates the findings of Djauhari (2017), who researched this topic.

3. Research Methodology

Network analysis focuses on monitoring subtle changes as the system evolves and measuring the significance of each factor in the complex system. When dealing with interconnected items to grasp the true behavior of each dimension, network analysis can be utilized to identify the most influential items (Sharif et al., 2012). This is achieved through established methods such as correlation network analysis and the MST.

Network analysis starts with a correlation matrix. A correlation matrix is able to show that relationship clearly and concisely. It is wieldy used for quantifying the interaction among objects (Barabási, 2009; Boccaletti et al., 2006; Dorogovtsev & Mendes, 2002). A correlation network-based approach is a new method that will help classify and utilize the significant information included in the matrix. The relationship between factors is constructed in the form of a network visually, which is extracted by the MST based on correlations matrix. Therefore, defined similarity measure based on correlation is an initial point for further network analysis.

The first subsection concentrates on recognizing the factors of student satisfaction as the primary consideration.

3.1. Data Collection

A literature review reveals that student satisfaction leads to three behavioral intentions: (i) satisfaction with support and adjustment to the virtual environment, (ii) satisfaction with the interaction in online classrooms, and (iii) satisfaction with the study program development. To assess student satisfaction in online learning during COVID-19, twenty-four items were developed based on these three behavioral intentions.

The study includes undergraduate students at Shiraz university who are specifically in their third and fourth years of study. The questionnaire comprises 24 characteristics organized into three dimensions of student satisfaction factors. Of these, the initial 10 pertain to satisfaction concerning support and adaptation to the virtual environment. The following eight questions focus on satisfaction with interaction in the virtual classroom, and the subsequent seven questions address satisfaction with the development of the study program. Table 1 provides a detailed list of these 24 attributes.

Survey participants answered 24 questions that evaluated their satisfaction with the teaching-learning process. The assessment utilized a Likert scale with five options: from Very Dissatisfied to Very Satisfied.

3.2. Network Construction and information filtering

Before establishing a complicated network, we first study about the relationship among objects. In a network-based approach, a similarity measure is used to investigate network properties using a matrix, with a particular focus on similarity-based networks. These networks employ a similarity measure such as linear or Pearson's correlation ρ_{ij} between objects *i* and *j* (Conover, 1971; Hauke & Kossowski, 2011; Tan et al., 2004). The basic formalism of the cross-correlation matrix involves the detailed representation of two variables.

Let *X* be a random vector of dimension *p* having positive definite covariance matrix $\Sigma = (\sigma_{ij})$. The correlation coefficient between components of *X*, specifically the *i*-th and *j*-th components, is given by:

$$\rho_{ij} = \frac{\sigma_{ij}}{\sqrt{\sigma_{ii}\sigma_{jj}}} \quad \text{for all } i, j = 1, 2, \dots, p$$

The coefficient ρ_{ij} quantifies the degree of linear relationship between the *i*-th and *j*-th variables. By definition, $|\rho_{ij}| \le 1$, and

 $\rho_{ij} = \left\{ \begin{array}{ll} 1 & \mbox{There is completely positive linear relationship} \\ 0 & \mbox{There is no linear relationship} \\ -1 & \mbox{There is completely negative linear relationship.} \end{array} \right.$

Due to this property, ρ_{ij} is commonly regarded as a natural measure of linear dependence among those variables. Now let $X \sim N_p(\mu, \Sigma)$ and $X_1, X_2, ..., X_n$ be a random sample of size *n* drawn from *X*. The sample covariance matrix is *S*. The matrix $S=(s_{ij})$ is the sample version of Σ . Thus, the sample correlation coefficient between the *i*-th and *j*-th variables is $\pi_{ij} = \frac{\pi_{ij}}{\sqrt{\pi_{ij}}\pi_{ji}}$. r_{ij} is the maximum likelihood estimate of ρ_{ij} . In this case, $\rho_{ij}=0$ if and only if both *i*-th and *j*-th variable are independent. Furthermore, if $\Omega=(\rho_{ij})$ represents the population correlation matrix, its sample version is $R=(r_{ij})$.

The correlation coefficient between *i*-th and *j*-th variables is calculated by ρ_{ij} for a pair of X_i and X_j items. Correlation coefficient ρ_{ij} for all pairs of items form a $n \times n$ symmetric matrix with diagonal elements equal to 1. This cross-correlation matrix shows the degree of correlation between all factors.

Now, with all the needed information, one can create an MST graph for all investigated factors. First, one

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1.	SATISFACTION WITH SUPPORT AND ADAPTATION TO ONLINE LEARNING			
SA1	University Strategies	Pandemic Management Assessment: Evaluating Student Satisfaction		
		with University Response Strategies		
SA2	Online Technology	Technology Support Satisfaction: Evaluating Student Contentment with		
		University Assistance in Online Technology		
SA3	Online Education	Virtual Learning Lecturer Commitment Assessment: Evaluating Stu-		
		dent Satisfaction with Instructor Dedication in Online Education		
SA4	Adaptation	Academic Adaptation Satisfaction: Evaluating Student Contentment		
		with Tutors' and Professors' Adjustments Amid the Pandemic		
SA5	Support Services	Beyond IT Support: Evaluating Student Satisfaction with Diverse Uni-		
		versity Support Services		
SA6	Technological Facilitation	Technological Facilitation: Evaluating Student Satisfaction with Lectur-		
		ers' use of Technology for Learning		
SA7	Career Lecturers' Pandemic Support	Pandemic Support from Career Lecturers: Assessing Student Satisfac-		
		tion with Program-Specific Assistance		
SA8	Understanding amidst Connectivity Is-	Lecturer Understanding amidst Connectivity Issues: Evaluating Student		
	sues	Satisfaction in the Face of Technical Challenges		
SA9	Virtual Modality Treatment Evaluation	Virtual Modality Treatment Evaluation: Assessing Student Satisfaction		
		with Changes in Lecturer Interaction and Support		
2.	SATISFACTION WITH	INTERACTION IN THE VIRTUAL CLASSROOM		
I1	Interactions in Online Environments	Virtual Mode Colleague Communication: Evaluating Student Satisfac-		
		tion with Interactions in Online Environments		
I2	Communication and Doubt Clarification	Open Expression of Doubts in Virtual Mode: Assessing Student Satis-		
		faction with Communication and Doubt Clarification		
I3	Flexibility of Lecturer Demands	Adaptability Assessment: Exploring Student Satisfaction with the Flex-		
		ibility of Lecturer Demands		
I4	Academic Motivation	Study Motivation Satisfaction: Assessing Student Contentment with		
		Personal Motivational Levels in Academic Endeavors		
I5	Modality Lecturer Communication	Virtual Modality Lecturer Communication: Assessing Student Satisfac-		
		tion with Interaction and Support in Online Learning		
I6	Class Reflection Time	Class Reflection Time Satisfaction: Assessing Student Contentment		
		with Opportunities for Contemplation during Virtual Learning		
I7	Lecturer Interest in Health and Well-being	Lecturer Interest in Health and Well-being: Assessing Student Satisfac-		
		tion with Faculty Concerns for Student Welfare		
I8	Class Duration	Class Session Duration Satisfaction: Assessing Student Contentment		
		with the Length of Virtual Class Sessions		
3.	SATISFACTION WI	TH THE STUDY PROGRAM DEVELOPMENT		
DS1	Online Learning	Virtual Modality Evaluation Satisfaction: Assessing Student Content-		
		ment with the Types of Assessments in Online Learning		
DS2	Timelines in Online Learning	Virtual Mode Schedule Compliance: Assessing Student Satisfaction		
		with Adherence to Timelines in Online Learning		
DS3	Ease of Understanding	Course Clarity in Virtual Learning: Assessing Student Satisfaction with		
		the Ease of Understanding in Online Courses		
DS4	Assessment Variety	Diverse Evaluation Methods in Virtual Learning: Assessing Student Sat-		
		isfaction with Assessment Variety in Online Education		

Table 1

Three Dimensions and Factors of Student Satisfaction in Online Learning During COVID-19

Tab	le	1
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Three Dimensions and Factors of Statient Sutisfaction in Online Learning During COVID-19 (Continuea)				
3.	SATISFACTION WITH THE STUDY PROGRAM DEVELOPMENT			
DS5	Pandemic Study Program	Pandemic Study Program Satisfaction: Assessing Student Contentmen		
		with Academic Experiences Amidst Challenging Times		
DS6	Course Content in Online Education	Content Compliance in Virtual Learning: Evaluating Student Satisfac		
		tion with Adherence to Course Content in Online Education		
DS7	Teaching Approaches	Virtual Modality Lecturer Methodology: Assessing Student Satisfaction		
		with Teaching Approaches in Online Learning		

Three Dimensions and Factors of Student Satisfaction in Online Learning During COVID-19 (Continued)

should create a distance matrix for all student satisfaction items. This matrix is composed of distances between every pair of items. The distance between items depends only on the correlation coefficient, which means it can be calculated easily and quickly. To obtain a distance based on correlation ρ_{ij} , Mantegna (1997) proposed the distance function:

$$d_{ij} = \sqrt{2 \left(1 - \rho_{ij}\right)}$$

The distance matrix $D=(d_{ij})$ defines the structure of a network that consists of 24 nodes, representing items. This network is fully connected, undirected, and weighted, with a total of 276 connections between its nodes.

An intriguing aspect emerges when we examine a distance matrix defined on a dioid. This matrix numerically represents a complex network, enabling us to add and multiply two networks. Imagine a complex network of n items as a connected, undirected, weighted graph with n nodes. The weight of the link between nodes a and b quantifies their complex relationship, acting as a dissimilarity or similarity score between nodes a and b.

A complete network can usually be depicted graphically, but visualizing all connections would result in a cluttered and difficult-to-read image, especially for small networks. Therefore, using an MST graph is more appropriate in this context. Network analysis using MST can effectively simplify the representation of the structures of 24 items based on *D*.

We identify the subdominant ultrametric (SDU) of *D*. The SDU establishes a taxonomy among items, commonly represented as a dendrogram. Then, we implement the procedure to identify the Forest and an MST, as suggested by Djauhari (2017), to obtain the filtered network.

Let D' denote the SDU of *D*, and Δ be the adjacency matrix of the forest.

Define $D^2=D \times D$, where multiplication is defined conventionally for elements in *D*. Additionally, define $a\otimes b=\max\{a,b\}$ and $a\otimes b=\min\{a,b\}$ for all elements *a* and *b* in D. If $D^2=D$, then $D^*=D^2$. Otherwise, go to next step. Compute $D^4=D^2 \times D^2$. If $D^4=D^2$, then $D^*=D^4$. Or else, compute $D^8=D^4 \times D^4$. The process continues until the t-th iteration, where $D^*=D^{2t}$. This procedure needs *t* iterations where $t \leq \frac{\ln(n)}{\ln(2)}$. It signifies an advancement in computational efficiency, specifically enabling a predetermined number of iterations.

Once D' is determined, Δ can be easily derived. Let Δ =D-D' (standard matrix subtraction). The adjacency matrix Δ is then obtained from D' by converting all zero off-diagonal elements to 1 and all non-zero elements to 0.

To find a Minimum Spanning Tree (MST), create T_1 by forming a sub-graph of the forest after removing all its leaves. If T_1 has no leaves, then T_1 itself is considered an MST, and combining T_1 with all previously removed leaves results in an MST of D. If T_1 still contains leaves, continue removing leaves iteratively until the k-th iteration, where T_k has no leaves. An MST of D is formed from T_k with all leaves that were previously removed.

According to this approach and the results of repeating the above steps twelve times, the adjacency matrix shows that the MST is unique, indicating that the forest consists of a single MST.

The MST is commonly employed to simplify the original network and condense the most important information. Utilizing Pajek software, widely endorsed for network analysis (De Nooy et al., 2011; Batagelj & Mrvar, 2003; Batagelj & Mrvar, 2004), al-

lows for graphical visualization of the simplified network. This visualization helps in understanding the complex network as a more straightforward structure.

Once the similarity measure among factors is established and the network is constructed, the focus shifts to interpreting its topology. Centrality measurement is a fundamental concept and one of the most extensively studied theories in the field of network analysis. Numerous measures have been developed to help in understanding the network by specifying its components and their interrelationships. They include degree, betweenness, closeness, eigenvector centralities, flow betweenness, the rush index, information centralities, the influence measures of Katz (1953), Hubbell (1965), Taylors (1969) measure and Hoede (1978), etc. Freeman in (1979) provided three basic measures (degree, betweeness, closeness) to answer the" what is centrality" question and for which he provided canonical formulations. Borgatti (2005, 2006) explored robustness of three centrality measures (degree, betweenness, closeness) in random graphs.

Network centrality refers to the position or location

of nodes within a network. It is used to identify and classify important factors within the network (Geisberger et al., 2008; Xu et al., 2009; Espino and Hoyos, 2010; Abbasi & Altmann, 2011). Degree centrality, betweenness centrality, and closeness centrality—key metrics in network analysis—each provide unique perspectives on the interactions among items within the network. Given that each centrality measure serves a specific role in identifying influential nodes, these three metrics will be utilized in this research.

4. Result and Discussion

In this section, we will use a graphical network of student satisfaction factors to highlight how dioid algebra can benefit network analysis.

Figure 1 displays the correlation-based Minimum Spanning Tree (MST) for the 24 factors across three dimensions of student satisfaction. This yields a network that is uncompleted, weighted, and undirected graph. Each factor is represented by its symbol and it is colored by its dimension classification.

Once the MST is identified, the network topology it represents is analyzed and summarized numerically



Figure 1 *Network Topology of 24 Student Satisfaction Factors*

using three widely used centrality measures, which constitutes a method for system analysis. We assess the outcomes derived from analyzing the network's topology. The characteristics of dimensions are classified into 24 factors. In Table 2, the 24 factors are classified based on centrality measures score.

Based on the degree centrality measure, the number of linkages ranges from 1 to 3, with none exceeding 3. The importance of factors is similar, and there is no significantly dominant factor. The subsequent connected factors include three linkages, comprising:

1. SA9 as Virtual Modality Treatment Evaluation (blue node),

2. SA4 as Academic Adaptation (blue node),

3. SA6 as Technological Facilitation (blue node),4. I8 as Class Session Duration Satisfaction (green node),

5. I3 as Flexibility of Lecturer Demands, and

6. DS4 as Diverse Evaluation Methods in Virtual Learning

According to the betweenness centrality measure in Table 2, SA9 (blue node) has the highest score (0.6) to others that show this factor is the most significant factor in the following sense. Therefore, SA9 plays an important role as a liaison that could affect the information among factors. The other high scoring factors are SA4, SA6 with highest score of betweenness and closeness centrality.

Table 2

24 Factors and	their	Central	ity	Measures
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No	Node	Degree	Betweenness	Closeness
1	SA1	2	0.087	0.209
2	SA2	1	0	0.174
3	SA3	2	0.498	0.245
4	SA4	3	0.549	0.25
5	SA5	1	0	0.202
6	SA6	3	0.533	0.235
7	SA7	2	0.443	0.213
8	SA8	2	0.474	0.23
9	SA9	3	0.601	0.255
10	I1	1	0	0.172
11	I2	1	0	0.151
12	I3	3	0.17	0.177
13	I4	2	0.166	0.198
14	I5	2	0.087	0.17
15	I6	1	0	0.151
16	Ι7	1	0	0.145
17	I8	3	0.312	0.205
18	DS1	2	0.403	0.195
19	DS2	2	0.166	0.155
20	DS3	2	0.087	0.153
21	DS4	3	0.379	0.177
22	DS5	1	0	0.134
23	DS6	2	0.087	0.137
24	DS7	1	0	0.121

Surprisingly, as we can see in Figure 1, the three groups of factors are clearly separated. All factors within a specific dimension are interconnected with each other and are largely associated with factors related to satisfaction with support and adaptation to online learning (represented as the blue node). For example Academic Motivation (I4) and Class Duration (I8) factors are linked to Technological Facilitation (SA6) and DS1 connected to SA7. Analysis indicates that the university should pay more attention to the following factors in online learning, as they have the lowest centrality measures. They are ranked in terms of dissatisfaction as follows: (a) Teaching Approaches, (b) Pandemic Study Program, and (c) Course Content in Online Education. Based on the three centrality measures, SA9, SA4 and SA6 are significant factors in ensuring student satisfaction amid the COVID-19 pandemic. These variables represent the following factors; Virtual Modality Treatment Evaluation, Academic Adaptation Satisfaction, Technological Facilitation, respectively.

5. Conclusion

The current paper aims to offer a comprehensive overview of how algebraic structures are applied in the field of network analysis. We demonstrated dioid algebra role in network and as we shown, its application in network analysis provides significant advantages, particularly in the context of using graph theoretical approaches. This is accomplished using established techniques of correlation network analysis and the Minimum Spanning Tree (MST).

The key contribution of this study lies in the analysis of a network that represents various dimensions of student satisfaction, with each dimension characterized by multiple factors. We created this network by examining correlations among these factors specifically within the context of online learning during the COVID-19 pandemic.

Our study proposes insights into the relationship between factors and the characteristics of the network. We introduced a method of network analysis and described the results of studies applying the correlation network-based approach. Additionally, we discussed the implications of this methodology. As a result of this study, three factors, namely: Teaching Approaches, Pandemic Study Program, and Course Content in Online Education have the lowest scores in all three measures of centrality. These should be carefully addressed by the university and educational services management to enhance educational services and increase student satisfaction.

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