

Analyzing Student Academic Trajectories through Mixed-Methods Social Network Analysis: An Organizational Perspective

Juan Pablo Salazar-Fernandez¹; Gustavo Otoniel Medina Retamal²; Iván Oliva Figueroa³

^{1,2,3}Universidad Austral de Chile, Chile, juansalazar@uach.cl, gustavo.medina@alumnos.uach.cl, ivanoliva@uach.cl

Abstract — *Low graduation rates and high dropout rates remain persistent challenges in STEM programs worldwide, often associated with a combination of demographic, academic, and institutional factors. While many studies focus on individual-level predictors of student success, fewer approaches analyze academic trajectories from cohort and organizational perspectives.*

This study examines student academic trajectories in engineering programs at Universidad Austral de Chile using anonymized institutional records from 2004–2015. The research combines database technologies, descriptive analysis, visualization tools, and Social Network Analysis (SNA) to identify structural patterns within student cohorts. Semi-structured interviews with academic stakeholders are conducted to interpret these patterns and relate them to institutional practices and program characteristics. The analysis shows that network-based visualizations can reveal structural patterns and recurrent configurations in selected student cohorts, which stakeholders interpreted as relevant to retention and dropout dynamics. These visualizations also supported discussions about program differences and mechanisms influencing student progression.

These results illustrate how network-based analysis can complement traditional approaches to studying academic trajectories and contribute to emerging curricular analytics methodologies that support data-informed curriculum management and institutional decision-making.

Keywords— *curricular analytics; social network analysis; academic trajectories; dropout*

I. INTRODUCTION

Student academic trajectories represent the temporal pathways through which students progress, experience delays, or withdraw from university programs. Analyzing these trajectories can reveal structural patterns associated with student persistence and dropout in higher education [1]. From an organizational perspective, trajectories emerge not only from individual characteristics but also from relational dynamics within student cohorts. While many studies rely on macro-level indicators such as socio-demographic characteristics or academic performance, recent research shows that meso-level factors related to students' university experiences and their social embeddedness within peer networks provide additional explanatory power for retention and dropout [2]. In recent years, this perspective has been increasingly explored within the emerging field of curricular analytics, which focuses on analyzing structural patterns in students' progression through academic programs in order to inform institutional decision-making and curriculum design.

A substantial body of research has examined student attrition and low graduation rates in higher education, particularly in STEM programs. Previous studies identify a wide range of associated factors, including psychological and motivational aspects, characteristics of courses and teaching practices, and demographic variables such as gender, age, and socioeconomic status [3]–[7]. These factors are often analyzed through students' perceptions of their academic experience, institutional conditions, and individual backgrounds.

One influential theoretical perspective is Tinto's model of student integration [8], which emphasizes the importance of academic and social integration into the university community. According to this framework, students who become better integrated into their academic and social environments are more likely to persist and succeed. Empirical studies also show that homophily based on gender, age, and academic performance is a recurring phenomenon in student networks [9], and that stronger integration within student cohorts may positively influence persistence, particularly during the early stages of university studies [4].

These findings highlight the importance of relational structures in shaping academic trajectories. Social Network Analysis (SNA) provides a useful methodological framework to study such structures, enabling researchers to analyze interaction patterns and structural properties within student cohorts using graph-based representations [10], [11]. However, SNA alone often provides limited insight into the mechanisms underlying observed network structures. To address this limitation, several studies combine SNA with qualitative approaches in order to interpret quantitative findings and better understand the processes shaping student interactions [10], [12]. This mixed-methods approach, known as Mixed Methods Social Network Analysis (MMSNA), has been applied in various educational contexts, including classroom interaction and online learning environments [13], [14].

Despite these advances, many learning analytics studies still struggle to translate analytical findings into institutional decision-making processes [15]. In particular, stakeholders such as program directors, administrators, and students are rarely involved in interpreting network-based results. Incorporating their perspectives may help contextualize emergent patterns and connect them to institutional practices and program characteristics [16], [17].

This study addresses this gap by analyzing student academic trajectories in undergraduate STEM programs at Universidad Austral de Chile (UACH) from an organizational perspective.

Using anonymized institutional records from 2004–2015, we combine Social Network Analysis with qualitative interviews involving multiple stakeholders. This mixed-methods framework allows us to identify structural patterns within student cohorts and interpret them through the perspectives of actors involved in the academic organization. By integrating network-based analysis with stakeholder interpretation, the study contributes to engineering education research and to the development of curricular analytics approaches aimed at understanding student progression and supporting institutional decision-making related to retention and program improvement.

The remainder of this paper is organized as follows. Section II reviews the relevant literature. Section III describes the data and methodology. Section IV presents the results of the analyses, and Section V discusses the main findings and implications.

II. LITERATURE REVIEW

A. Student Dropout in Engineering Education

Student dropout and low graduation rates remain persistent challenges in engineering education. Previous research identifies a wide range of factors associated with student attrition, including an unwelcoming academic climate, conceptual difficulties in core courses, low self-efficacy or self-confidence, insufficient academic preparation, limited interest or commitment to the discipline, and experiences of racism or sexism [18]. Economic considerations, such as lower perceived returns to tertiary education, as well as insufficient academic and social integration within the university environment, have also been associated with higher dropout rates [6].

Prior studies emphasize that attrition rarely results from a single factor. Instead, it emerges from the interaction of individual characteristics, academic conditions, and institutional contexts [5], [19]. For example, poorly structured curricula, insufficient mentoring, low-quality instruction, and exclusionary departmental cultures may significantly influence students' persistence in engineering programs [5], [19]. These findings suggest that student dropout should be understood not only as an individual outcome but also as a phenomenon shaped by the organizational and structural characteristics of educational programs.

B. Curricular Analytics and Academic Trajectories

In recent years, the field of Learning Analytics (LA) has developed rapidly as an approach for analyzing educational data in order to improve teaching, learning, and institutional decision-making in higher education [20]. Within this broader field, Curricular Analytics (CA) has emerged as a subfield that focuses on analyzing how curricular structures influence student progression and program outcomes [21], [22].

Curricular Analytics examines the interaction between students and curricular structures over time by analyzing course sequences, prerequisite structures, and patterns of student progression across programs. Within this perspective, academic trajectories represent structured patterns of progression through academic programs, reflecting the interaction between

curricular constraints, institutional structures, and student behavior [1], [23].

Several CA studies analyze student progression using data extracted from institutional information systems. For example, Process Mining techniques have been applied to analyze late-stage dropout by extracting knowledge from event logs in order to discover process models, verify conformance, and suggest improvements to academic processes [1]. While these approaches typically represent academic progression as sequences of events or processes, they often overlook the relational dimension of student trajectories, such as peer interactions and social integration within cohorts.

Understanding academic trajectories therefore requires not only analyzing curricular structures but also examining the relational environments in which students progress through their programs.

C. Mixed Methods Social Network Analysis

Social Network Analysis (SNA) provides a methodological framework for studying relational structures among students by representing interactions as networks and analyzing their structural properties [10], [11]. In educational settings, SNA has been widely used to examine collaboration patterns, peer influence, and social integration within learning communities.

However, SNA alone often provides limited insight into the mechanisms underlying observed network structures. To address this limitation, researchers increasingly combine SNA with qualitative approaches in order to interpret quantitative findings and better understand the processes shaping student interactions [10], [12]. This approach, known as Mixed Methods Social Network Analysis (MMSNA), integrates network analysis with qualitative data sources such as interviews, observations, or document analysis.

The motivations for combining methods in MMSNA are typically categorized as triangulation, complementarity, and development [24]. Triangulation refers to comparing findings obtained through different methods in order to identify convergence or divergence. Complementarity involves integrating qualitative and quantitative findings to capture the complexity of the phenomenon under study. Development refers to using results from one method to inform or refine subsequent phases of the research.

In mixed-methods research, methodological integration is often described using the terminology of concurrent and sequential combinations of quantitative (Quan) and qualitative (Qual) approaches, indicating the order and manner in which the methods are integrated. For example, a triangulation strategy based on a concurrent Quan + Qual design involves conducting quantitative and qualitative analyses simultaneously and comparing their results during the interpretation stage.

Guidelines for MMSNA research have been proposed through frameworks such as PRICE, which identifies five key principles: participatory, reflexive, integrated, critical, and ethical research practices [25]. These principles emphasize stakeholder participation, contextual awareness in knowledge production, integration of methodological approaches, critical

reflection on power dynamics, and adherence to ethical standards. Together, these guidelines support the systematic and responsible implementation of MMSNA studies and encourage the meaningful involvement of stakeholders in interpreting network-based findings.

D. Research Gap

Despite the growing body of research on student dropout, curricular analytics, and social network analysis in educational contexts, these perspectives are rarely integrated within a single analytical framework. Existing studies tend to focus either on curricular structures and event-based representations of academic progression or on relational dynamics within learning environments. As a result, limited attention has been given to how relational structures within student cohorts interact with institutional and curricular contexts to shape academic trajectories over time.

Addressing this gap requires approaches that combine structural analysis of student networks with qualitative insights from institutional stakeholders in order to contextualize and interpret emergent patterns of student progression and dropout.

III. METHODS

This section explains the methodology used to investigate the causes of low graduation and high dropout rates in STEM programs at UACH. Our methodology takes as references the PRICE set of good practices [25], applying them to themes like ethical principles of data collection and the overall process that looks for the involvement and active participation of stakeholders in each stage of the study.

A. Data sources

The main data source for this study is a collection of anonymized student records from 2004 to 2015, compiled from the STEM programs at the Universidad Austral de Chile. The records include information such as student ID, gender, program, mathematics PSU (Chilean university selection exam), percentile rank in mathematics PSU, place of origin, year of admission, final status - categorized as early dropout (withdrawal during the first two years), late dropout (withdrawal after the second year), on-time graduation (completion within the nominal program duration), and late graduation (completion after exceeding the nominal duration), funding source (scholarship, use of a government loan or self-funding), and income quintile. The study focuses on three engineering programs: Computer Science and Software Engineering (ICI), Civil Engineering (OCC), and Electronic Engineering (ICE), as we have more data on these programs.

The secondary data source for this study is a series of interviews with various stakeholders who are involved in the student dropout and retention phenomenon. These stakeholders include teachers, students, program secretaries, directors of schools of engineering, and other relevant actors at the organizational level such as psychologists and counselors. The interviews were recorded and transcribed, or taken on paper,

with the initial permission and confirmation of every stakeholder. The aim was to elicit their opinions, perceptions, experiences, and suggestions regarding the causes and consequences of student dropout and retention in at least two stages of this study.

Regarding the results of this paper, they are not exhaustive of the material used but illustrative of the overall work and capacities of the approach formulated. We specifically focus the final cases on programs that allow us to follow up in the long run and give us sufficient information for the analysis.

B. Data collection procedures

We conducted two principal phases in our study, where the first one was with a triangulation approach and a concurrent Quan + Qual model. In this way, we gathered initial information that helped us formulate the second complementary phase, combining the results of the first phase with a qualitative study in a sequential way.

The initial semi-structured interview phase involved interviewing a sample of stakeholders from each group (teachers, students, secretaries, directors, etc.), using a set of open-ended questions that were designed to obtain their initial conceptions of the reasons for student dropout and retention. The questions also asked about their roles, responsibilities, expectations, challenges, and recommendations regarding student success in engineering education. The interviews were recorded and transcribed for later analysis.

Quantitative data were extracted from the university data lake, processed in an Oracle SQL database, anonymized, transformed into CSV files by program, and converted into GEXF format for analysis in Gephi. This process enabled the construction of the network models while preserving data integrity and confidentiality. The second interview phase involved a writing assessment with the majority of previous and new stakeholders from each group, using a set of graphs and diagrams to illustrate the network structures and patterns selected in the SNA stage. The questions aimed to interpret, clarify, contextualize, or challenge the results obtained from the first phase, as well as obtain their feedback and suggestions for improvement.

The visualizations were not treated as self-sufficient evidence, but as boundary objects that enabled stakeholders to articulate interpretations, compare cases, and connect structural patterns with institutional experience.

C. Data analysis methods

The SNA phase involved analyzing the quantitative data from the student records using database technologies, visualization tools, and statistical methods. The analysis aimed to explore relationships and patterns among the variables and to generate interpretable visual configurations for stakeholder discussion. At the same time, it involved constructing network graphs based on different criteria such as program, gender, place of origin, funding source, income quintile, mathematics PSU, percentile rank in mathematics PSU, final status, etc.

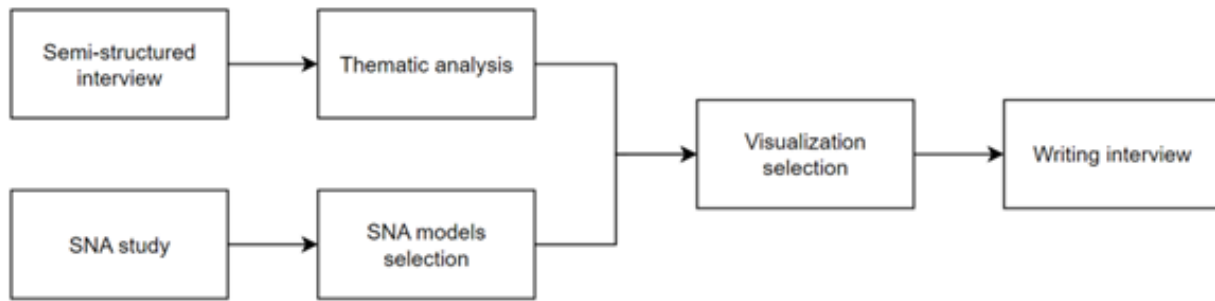


Fig. 1. Methodology approach

The network graphs were created using Gephi software and were used to explore structural properties of the networks, with particular attention to cluster formation, modularity-based communities, and visually identifiable patterns of cohort fragmentation. We formulated at least six different models of visualization and defined some restrictions for every case. The

two principal restrictions were that every student needs to have a PSU score not equal to 0, in order to get a better visualization of PSU in general, and on the other hand, to only show a relationship between two nodes (students) if they have a weight equal to or above 3 (meaning that two students need to have more than two classes together to show a relation in the graph).

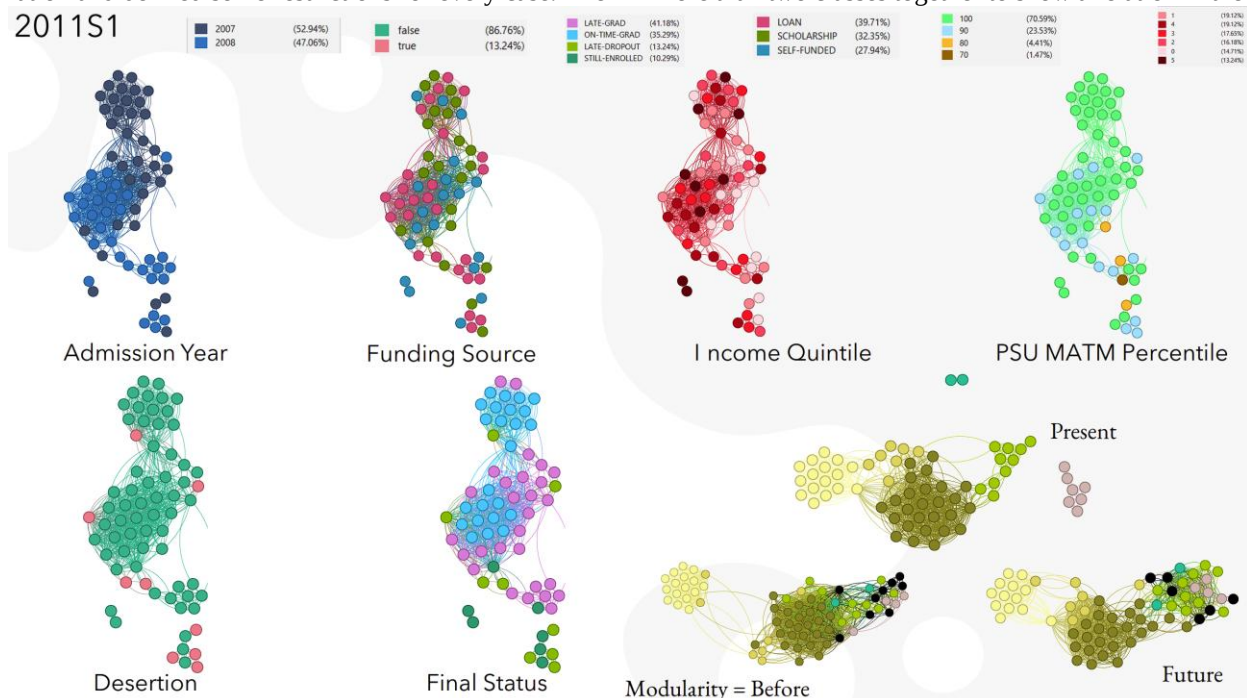


Fig. 2. SNA on the data

Given the exploratory and stakeholder-oriented purpose of the study, the network analysis was used primarily as a visual-analytical device rather than as a predictive or inferential model. The aim was not to estimate causal effects or construct a statistical dropout model, but to identify interpretable structural configurations that could be discussed with institutional stakeholders. Accordingly, the results should be read as pattern-based interpretations of selected cases, supported by stakeholder validation, rather than as generalizable statistical estimates.

IV. RESULTS

In this section, we present the main results from each segment of the implemented MMSNA stages. Each phase is given its own subsection, where we detail pertinent findings.

In particular, we've narrowed down the results from the first phase to align with those of the second phase. The results should

be interpreted at three complementary levels: first, as observed network configurations derived from co-enrollment data; second, as stakeholder interpretations elicited through the writing assessment; and third, as organizational implications for curriculum management. The study does not seek to produce predictive estimates of dropout, but to explore how network-based representations can support institutional interpretation of academic trajectories.

A. Phase One: Thematic Analysis Results from Semi-Structured

Interviews Through the course of our study, qualitative data was accumulated from semi-structured interviews and examined through thematic analysis. To illustrate which stakeholders played a significant role in shaping each theme, we will initially present a table detailing their contributions. Following this, we will delve into each theme, outlining the overarching findings as they emerge from the interviews.

TABLE I
Key Stakeholders for Each Theme

Theme	Key Stakeholders
Economic Factors	Secretary, Director, Psychologist
Benefits	Secretary, Director, Educational Psychologist
Performance Indicators	Director, Basic Sciences Teacher, Educational Psychologist
Course Failures	Basic Sciences Teacher, Educational Psychologist, Psychologist, Student
Social Skills	Psychologist, Educational Psychologist, Basic Sciences Teacher, Student
Entrance Scores	Director, Secretary, Basic Sciences Teacher, Student

- Economic Factors: Stakeholders frequently referred to students' economic status as an important factor influencing academic performance. Notably, students from lower socioeconomic backgrounds often faced multiple challenges, although these were not always determinative of their performance or continuation in university.
- Benefits: Stakeholders perceived students admitted through the PACE program as being advantaged due to the tools provided to them. Loss of tuition-free education was identified as a significant event, particularly impacting lower quintile students.
- Performance Indicators: First-year academic performance was frequently associated with a higher likelihood of persistence. Stakeholders identified early academic results as a key indicator of a students' ability to cope with academic challenges.
- Course Failures: Failure rates in foundational courses, particularly algebra and geometry during the first semester, were identified as strong predictors of later academic difficulties.
- Social Skills: Stakeholders affirmed that strong social skills positively impact university persistence by creating a comfortable and conducive environment. Conversely, students lacking such skills often reported distress and lower academic performance.
- Entrance Scores: Entrance examination scores, although not perfectly correlated with outcomes, were viewed as indicators of a students' academic preparation and potential success in their programs.

B. Phase One: SNA selection methods and approach

In the development of this study, we created different models, trying to encompass the majority of visualization tools in Gephi, like the timeline for semester to-semester filtering on data or different layout options like Force Atlas 2 or the ordered graph layout for a dimensional categorization of information. In general, we formulated at least four different types of visualizations, but in the end, we decided to stick with a single approach to the data.

Our final visualization approach took into account the final purpose of integrating the results with the second phase of interviews, so it couldn't be too complex or simple in a way that conveyed minimal information. That's why the final decision was to use the Force Atlas 2 for the layout, with the lin-log option (which makes the clusters tighter) and the prevent

overlap option, in order to get a better identification of singular nodes. At the same time, it was used with the Gephi Create Time Interval option to formulate a semester-to-semester study in a dynamic way. We decided to use a selection of two consecutive cohorts, in a way to see the evolution of relationships in the students through time, of those that are in their ideal semester courses, and those that get stuck in first or second semester courses.

Two specific restrictions were raised: not allowing students with PSU equal to 0 and the edge weight to be equal or more than three. The nodes without relationships were left out of the graphs before the layout. These decisions were made in order to reveal more relevant data in the graphs and to be consistent in our overall methodology.

We chose two models with four cases each, taking aspects like the knowledge of the stakeholders that we acquired in our first interview into account and the amount of information the visualizations should convey.

First Model: Fourth Semester Analysis. Our first model emphasizes two aspects: the phenomenon of sophomore dropout and the shared and contrasting tendencies of dropout across STEM programs. We chose four cases to illustrate these aspects: OOC 2010–2011, ICE 2011–2012, ICI 2004–2005, and ICI 2009–2010.

As can be seen in the example, for each case, we have four graphs. The first one, at the top left, shows the distribution of students according to their entrance cohort. In this case, 2004 students are sophomores, while 2005 students are in their first year of university. Then, at the top right, we have the desertion, where false (green) means that the student could graduate and true (pink) means that the student dropped out at a certain point in their program. The Final status graph at the bottom right shows if the dropout was early (first two years) or late (after two years) or if the graduation was on time or late (past the eleven semesters of the STEM programs selected). Another option in the final status is still enrolled, as seen in other cases (given that our database only shows information until 2015). The Modularity graph at the bottom left shows clusters defined by the Gephi community detection tool (called Modularity) and is an optional way to define clusters mathematically.

The graphical analysis reveals the separation of students according to their academic semester (clearer in some programs than others). Each cluster reveals different tendencies in terms of dropout and progression rate, bringing to light some key

observations. The first cluster (light blue in modularity) represents students (principally first-year students) taking their first academic semester courses (Typically failing to pass geometry or algebra), showing the highest dropout rates. In the selected visualization, this subgroup was almost entirely composed of students who eventually dropped out; however, this should be interpreted as a descriptive pattern within the analyzed cases rather than as a predictive probability.

The second cluster (orange and pink in modularity) represents students progressing normally through their first year. Although dropout is less common than in the first cluster, it remains a significant concern. A prominent trend is that sophomores lagging by two semesters present the highest dropout rate, despite their smaller proportion.

The third and fourth clusters (green in modularity) primarily consist of sophomores, most of whom persist in their university studies. Determining which is the third or fourth semester becomes challenging if it is completely separated from the second-semester cluster.

Second Model: PSU-Quintile-funding. The second model of our analysis focuses on the relevance of PSU scores, quintile classification, and financial support in understanding student dropout during the initial three years of ICI 2009–2010.

PSU scores, particularly in the first semester of 2009, indicate that students in areas with higher red concentrations (indicative of high PSU scores) tend to persist. However, by the

second year, low PSU percentile students in the yellow cluster exhibit total dropout. Interestingly, high PSU score students also desert, emphasizing that a high PSU percentile does not necessarily guarantee persistence.

Regarding financial support, we find a high desertion rate among loan students in the first semester. At the same time, we find a high graduation rate for self-funded students, even though they have a smaller proportion in contrast to scholarship or loan students.

Although the quintile may suggest higher PSU scores, this is not categorical. In the second year, we find that low PSU percentile students in clusters with high PSU concentration trends tend to persist, while high PSU percentile students in clusters with low PSU concentrations tend to desert. Our models, therefore, reveal intricate patterns of student desertion and progression within STEM programs. The early identification of these patterns may provide qualitative warning cues for institutional discussion and preventive actions.

C. Phase two: Final writing assessment interview

The final phase used a writing assessment rather than semi-structured interviews, because the visualizations required stakeholders to examine, compare, and synthesize complex patterns. The assessment included an introductory exercise on graph interpretation followed by the evaluation of selected models and cases.

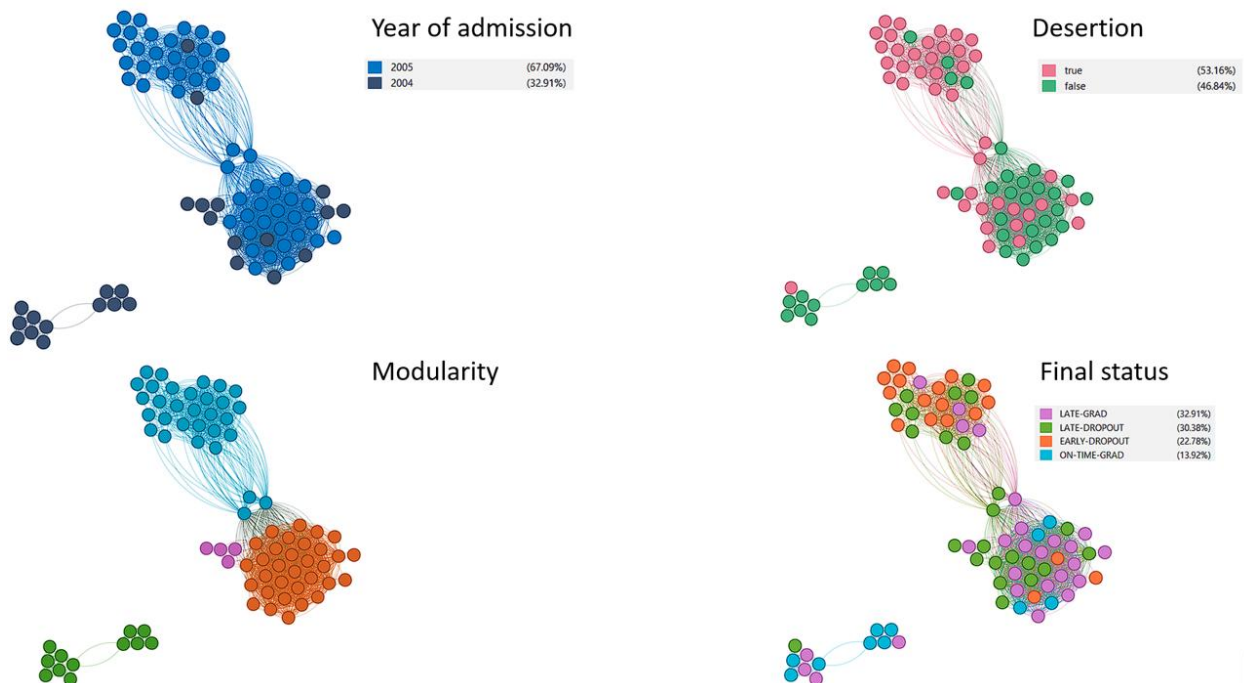


Fig. 3. Fourth semester of ICI 2004-2005

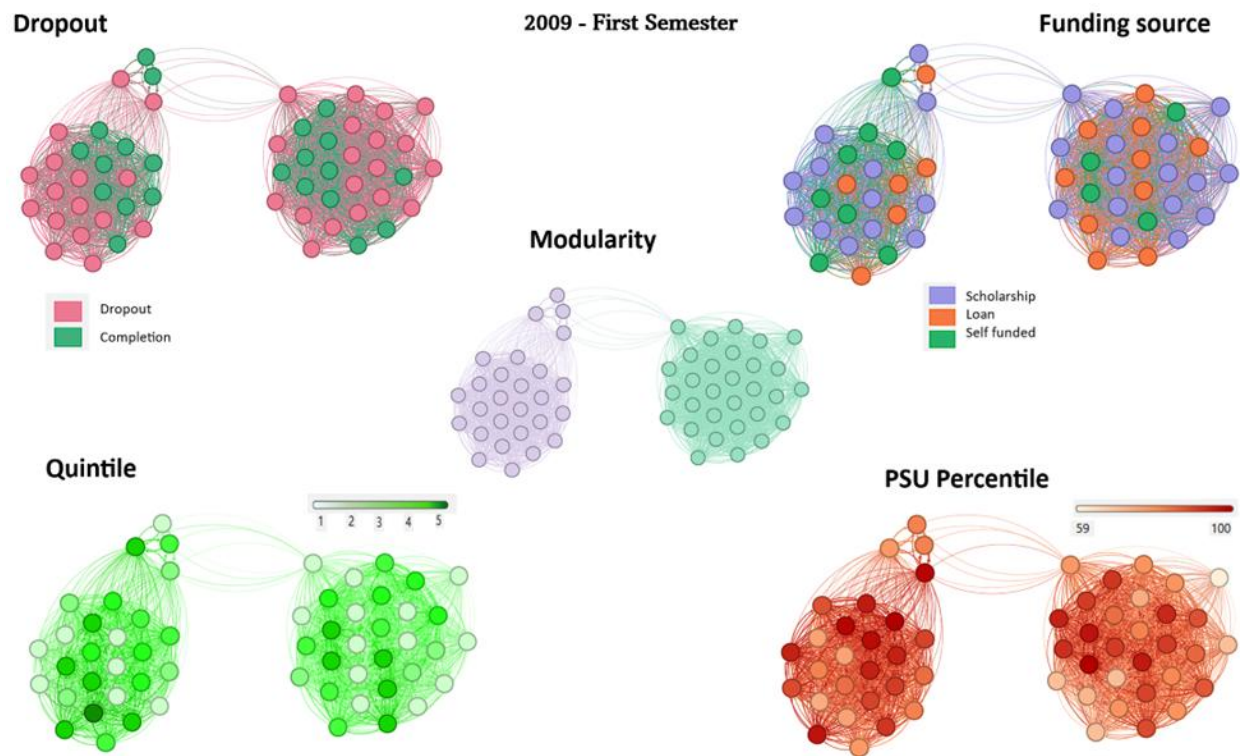


Fig. 4. First semester ICI 2009-2010

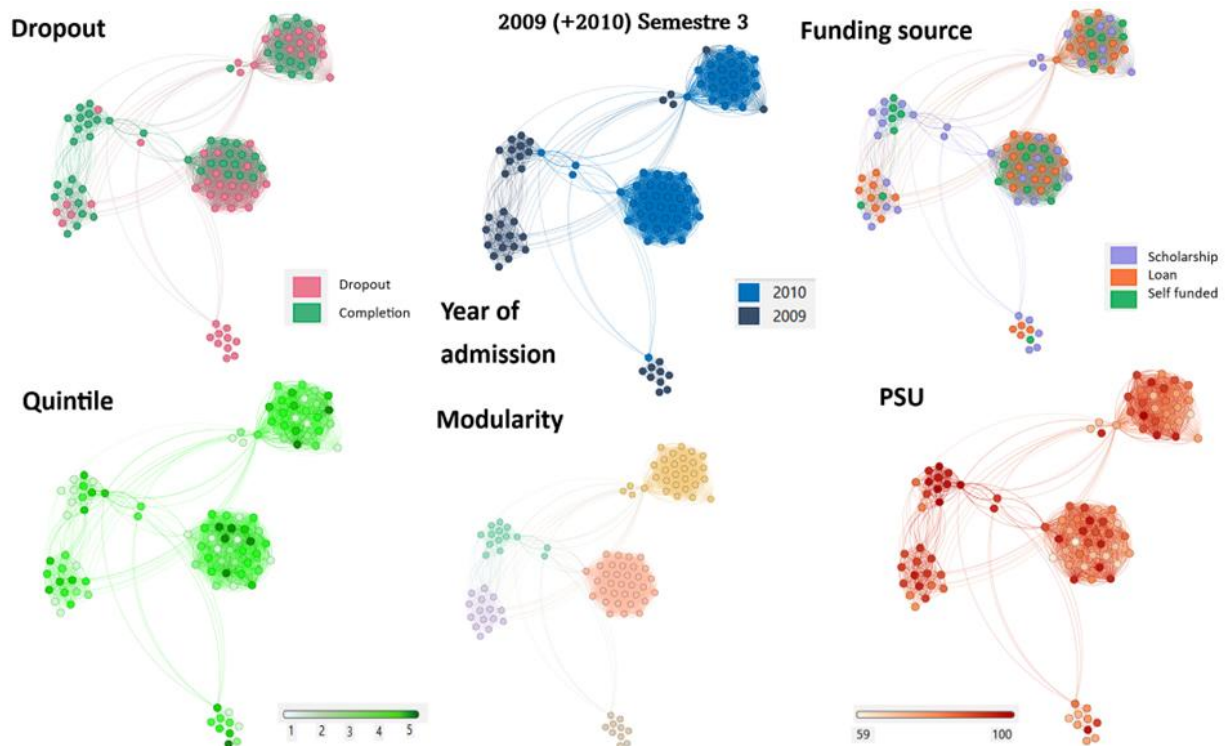


Fig. 5. Third semester ICI 2009-2010

Part one: Introductory exercises. Our objective in this introduction was to show the stakeholders a first glance of the potential cases that they would evaluate in an example graph with few nodes and relations, based on real cases but smaller in size.

What we showed them was a simplified example of a third semester of a STEM program, with an explanation of the colors (green=graduation, pink=dropout, dark shade of red = high PSU, light shade of red = low PSU), the weight of the relations (how many courses two students take together), and the number

over them (In the left is the PSU score, and in the right is the ID of a student).

Firstly, they needed to identify clusters, characterize them, and then interpret what this means in real-life scenarios. In the first graph of desertion (the one on the right), we proposed three questions:

1. How many clusters (groups with high interrelation) do you find in the graph?
2. What can you say about each cluster?
3. What do you think of cases 1 and 3? What about the one with ID 0?

Then, for the PSU graph (the one on the left), we try to make them realize how to compare both graphs with the color differences in a way to better understand the reality of each student. For this graph, we formulated another three questions:

1. How does it contribute to your previous findings or conclusions?
2. What can you say about each cluster?
3. What speculation can be made regarding node ID 4? Does it remind you of any real-life cases you have encountered?

There were two stakeholders with little knowledge of this kind of study, but in general, stakeholders could make use of these examples to delve deeper into how to obtain information from these visualizations and interpret them in their context as students of STEM programs. Finally, it proved to be essential for many of them to address real-life scenarios.

First Model: Fourth Semester Analysis.

Inter-cluster Connectivity and Dropout: A basic science teacher and an educational psychologist observe that students who serve as bridges between two clusters tend to drop out. These students might focus more on major-specific courses, neglecting the basic science courses.

Descriptive Patterns of Deserter Groups: A basic science teacher highlights that in ICI, it is not clear which case has a higher dropout rate compared to OOC. In ICE, there is isolation between advanced and delayed students, and clusters related to desertion can be observed. Also highlights that in some cases, modularity proves to be more useful.

Variability in Retention: An ICI Teacher states that there seems to be more variability in 2009–2010 compared to 2004–2005. In OOC, there is less delay, and in ICE, the dropout rate is clearly seen among delayed students. It also describes specific retention patterns for different cohorts, such as the 2010–2011 OOC group, which advances together with fewer dropouts.

Student Characteristics: The ICI Secretary discussed the characteristics of students according to their programs and the common conditions that prevent the continuity of studies. An educational psychologist identifies different patterns within cohorts, like the 2005 ICI students divided between repeaters and those who pass.

Impact of Study Habits and Course Burden: An educational psychologist suggests that smaller groups with fewer subjects may have less desertion because students can focus on the subjects they can pass. An ICI secretary points out the importance of dedicating time to studies rather than distractions.

Social Factors and Personal Characteristics: An ICI secretary highlighted several personal and social factors affecting continuity of studies, including low tolerance for frustration, neurodevelopmental conditions such as attention-deficit/hyperactivity disorder (ADHD) and autism spectrum disorder (ASD), excessive gaming, and the need to balance work and academic responsibilities.

Second Model: PSU-Quintile-funding

Group Separation and Heterogeneity: A basic science teacher and the director of the pedagogy center of basic sciences (CDCB) both observe natural separation into heterogeneous clusters in the first and third semesters.

Impact of Financing: An ICI teacher and two educational psychologists highlight the influence of financing on student abandonment. Students with credit financing tend to abandon school more quickly. An ICI teacher and an educational psychologist mention the role of income and scholarships. Students from higher-income backgrounds or from lower income backgrounds with scholarships tend to have better emotional and psychological handling and prior academic preparation.

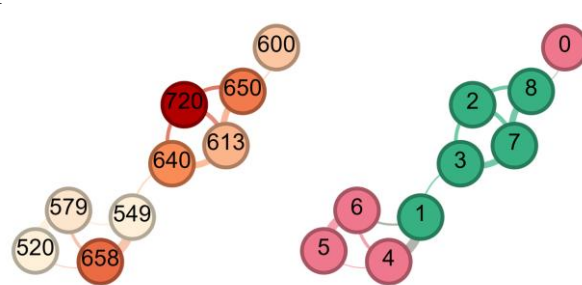


Fig. 6. Introductory example

Relationship between PSU Scores and Retention: An ICI teacher, a basic science teacher, and two educational psychologists discuss the correlation between PSU scores and student retention. Higher PSU scores indicate better persistence in some cases.

Abandonment Patterns: An educational psychologist notes a group of repeaters who abandon the third semester.

Academic Preparation and Study Habits: An ICI secretary and an educational psychologist emphasize the importance of academic preparation and study habits. Students with better academic preparation and study habits tend to persist, regardless of financing or PSU scores.

Suggestions for future investigation. Some stakeholders show concern for different aspects, like the lack of importance in the axis in our graphs, which could be used to gain stakeholders space intuition.

We find that there is a tendency for stakeholders related to mathematics, from teachers to students, to understand the graphs more quickly than those related to administration or counselling areas. Although the reasons for this difference were not fully clear, both groups ultimately produced useful interpretations despite the initial complexity. This could be

something to take into account in future studies, especially when selecting the visualizations for the interviews.

There is a need for solid visualizations with standard sizes, places, and colors for each graph. These differences added complexity to our visualizations. In general, the average time for the writing interview was 1:30 to 2 hours, which hopefully could be improved by better visualization standards.

V. DISCUSSION

This study explored student academic trajectories through the integration of SNA and qualitative stakeholder interpretation within an MMSNA framework. The results suggest that visualizing structural patterns within student cohorts can provide insights into progression and dropout that are difficult to observe using traditional academic indicators alone, complementing research on student persistence that emphasizes the interaction between individual and institutional factors [6].

A first important contribution of the study is the identification of structural patterns associated with delayed progression and dropout. In the Fourth Semester Analysis model, students who remain enrolled in first-semester courses during their second academic year appear, in the selected cases, to be strongly concentrated among later dropout outcomes. This pattern suggests that academic delay and cohort fragmentation may play an important role in shaping student trajectories. Rather than functioning as a predictive estimate, this pattern provides an organizational signal: prolonged attachment to first-semester course structures may indicate cohort fragmentation and increased vulnerability. From an organizational perspective, this finding highlights how curricular structures and course sequencing may unintentionally contribute to the isolation of delayed students, reducing their integration with their original cohort and increasing their vulnerability to dropout.

These results resonate with established theoretical perspectives on student persistence, particularly Tinto's model of academic and social integration [8]. According to this framework, students who achieve stronger academic and social integration within the university community are more likely to persist in their studies. In the present study, the network visualizations reveal clusters that correspond to different stages of academic progression, suggesting that students who become disconnected from their cohort structure may experience weaker integration within the academic environment.

An additional insight emerging from the stakeholder interpretation concerns the role of students occupying bridging positions between clusters. In several cases, stakeholders observed that students connecting two clusters—often representing different academic progression stages—tended to drop out more frequently. One possible explanation is that these students experience competing academic demands, such as simultaneously taking introductory and advanced courses, which may increase academic pressure and reduce their effective integration within a stable peer group. Previous research on social networks suggests that relational structures such as homophily and cohesion play a significant role in

shaping interaction patterns within groups [11]. In this context, network position may provide an additional interpretive layer when analyzing mechanisms of student persistence and dropout.

The PSU–Quintile–Funding model provides further insights regarding the role of prior preparation and financial conditions in shaping academic trajectories. The results suggest that entrance examination scores (PSU) appear to be particularly relevant during the first year of study but become less predictive of student persistence in later semesters. This finding is consistent with previous studies showing that early academic preparation may influence students' adaptation to university studies, while long-term persistence is often shaped by a broader combination of academic, social, and institutional factors [6]. At the same time, the analysis suggests that students relying on loan-based financial support tend to abandon their studies earlier, highlighting the potential impact of financial pressure on student persistence.

These findings also illustrate how network-based representations of student trajectories can complement existing approaches within the field of curricular analytics. Curricular analytics aims to analyze how curricular structures influence student progression through academic programs in order to support institutional decision-making and curriculum improvement [1], [21]. While many curricular analytics studies focus on course sequences or event-based representations of academic progression, the present study demonstrates that relational structures among students may provide an additional analytical layer for understanding how curricular organization interacts with student progression. In particular, the clustering patterns observed in the network visualizations reflect how curricular constraints, course sequencing, and cohort organization jointly shape academic trajectories.

Another important contribution of this study concerns the methodological role of MMSNA in bridging quantitative and qualitative perspectives. The integration of stakeholder interviews proved essential for interpreting the network patterns observed in the SNA stage. While network visualizations reveal structural configurations within student cohorts, the qualitative interpretation provided by teachers, administrators, and educational psychologists helps contextualize these patterns within institutional practices and student experiences. This methodological integration aligns with previous research on mixed methods social network analysis, which emphasizes the importance of combining quantitative network data with qualitative insights in order to better understand the mechanisms underlying relational structures [10], [24].

In addition, the process of presenting network visualizations to stakeholders highlighted the importance of designing representations that balance analytical richness with interpretability. Visualizations that were too complex created barriers for interpretation, while overly simplified representations failed to convey relevant structural information. These observations are consistent with recent research in learning analytics, which stresses the need to translate analytical outputs into forms that are accessible and meaningful for institutional decision-makers [15]. Future studies should

therefore consider the development of visualization standards that facilitate stakeholder interpretation while preserving the analytical value of network models.

Despite the insights provided by this study, several limitations should be acknowledged. First, the dataset covers student records from 2004 to 2015. While this long time span makes it possible to observe complete academic trajectories, the findings should not be interpreted as current estimates of dropout rates. Rather, they provide evidence of structural patterns of progression, delay, and cohort fragmentation that may remain relevant for curriculum management. Given subsequent changes in higher education—such as the replacement of the PSU examination by the PAES test, changes in financial aid policies, and the impact of the COVID-19 pandemic—future research should replicate and extend the analysis using more recent data to assess whether the magnitude and distribution of these patterns have changed. Second, the network structures analyzed in this study are derived from shared course enrollment rather than from direct social interaction data. While co-enrollment networks provide a useful proxy for potential peer interaction and cohort structure, they may not fully capture the complexity of students' social relationships. This distinction is important because the study's organizational focus concerns how curricular structures place students together or separate them over time. Future research could integrate additional data sources, such as collaboration networks or digital learning platforms, in order to provide a more comprehensive representation of student interaction patterns.

In conclusion, the present study demonstrates the potential of Mixed Methods Social Network Analysis for studying academic trajectories in engineering education. By combining network-based analysis of student cohorts with qualitative stakeholder interpretation, the approach provides a richer understanding of how structural and organizational factors influence student progression and dropout. These insights can contribute to the development of data-informed strategies aimed at improving student retention and supporting continuous improvement processes in engineering education programs.

VI. ACKNOWLEDGMENTS

This study was conducted using anonymized data, provided by Universidad Austral de Chile.

REFERENCES

- [1] J. Salazar-Fernandez, M. Sepúlveda, J. Muñoz-Gama, and M. Nussbaum, "Curricular analytics to characterize educational trajectories in high-failure rate courses that lead to late dropout," *Applied Sciences*, vol. 11, no. 3, p. 1436, 2021.
- [2] S. C. Matz, C. S. Bukow, H. Peters, et al., "Using machine learning to predict student retention from socio-demographic characteristics and app-based engagement metrics," *Scientific Reports*, vol. 13, p. 5705, 2023. doi:10.1038/s41598-023-32484-w.
- [3] R. S. dos Santos, M. A. Ponti, and K. R. da Hora Rodrigues, "The use of digital reports to support the visualization and identification of university dropout data," in *Proc. Int. Conf. Human-Computer Interaction*, Cham, Switzerland: Springer, 2022, pp. 308–323.
- [4] R. Mauldin, L. Barros-Lane, Z. Tarbet, K. Fujimoto, and S. Narendorf, "Cohort-based education and other factors related to student peer relationships: A mixed methods social network analysis," *Education Sciences*, vol. 12, no. 3, p. 205, 2022.
- [5] M. Meyer and S. Marx, "Engineering dropouts: A qualitative examination of why undergraduates leave engineering," *Journal of Engineering Education*, vol. 103, no. 4, pp. 525–548, 2014.
- [6] C. Aina, E. Baici, G. Casalone, and F. Pastore, "The determinants of university dropout: A review of the socio-economic literature," *Socio-Economic Planning Sciences*, vol. 79, p. 101102, 2022.
- [7] E. Höhne and L. Zander, "Belonging uncertainty as predictor of dropout intentions among first-semester students of the computer sciences," *Zeitschrift für Erziehungswissenschaft*, vol. 22, pp. 1099–1119, 2019.
- [8] V. Tinto, "Dropout from higher education: A theoretical synthesis of recent research," *Review of Educational Research*, vol. 45, no. 1, pp. 89–125, 1975.
- [9] M. McPherson, L. Smith-Lovin, and J. Cook, "Birds of a feather: Homophily in social networks," *Annual Review of Sociology*, vol. 27, pp. 415–444, 2001.
- [10] D. Froehlich, M. Rehm, and B. Rienties, "MMSNA: An introduction of a tale of two communities," in *Mixed Methods Social Network Analysis*, 2019, pp. 1–9.
- [11] R. Kalisa, B. Rienties, A. I. Mørch, and A. Kluge, "Social learning analytics in computer-supported collaborative learning environments: A systematic review of empirical studies," *Computers and Education Open*, vol. 3, p. 100073, 2022.
- [12] A. Tashakkori and J. Creswell, "The new era of mixed methods," *Journal of Mixed Methods Research*, vol. 1, no. 1, pp. 3–7, 2007.
- [13] B. Rienties, Y. Hélot, and D. Jindal-Snape, "Understanding social learning relations of international students in a large classroom using social network analysis," *Higher Education*, vol. 66, pp. 489–504, 2013.
- [14] B. Rienties, D. Tempelaar, P. Van den Bossche, W. Gijssels, and M. Segers, "The role of academic motivation in computer-supported collaborative learning," *Computers in Human Behavior*, vol. 25, no. 6, pp. 1195–1206, 2009.
- [15] L. Márquez, V. Henríquez, H. Chevreux, E. Scheihing, and J. Guerra, "Adoption of learning analytics in higher education institutions: A systematic literature review," *British Journal of Educational Technology*, vol. 55, no. 2, pp. 439–459, 2024.
- [16] S. Toraman, K. Cox, V. Clark, and J. Dariotis, "Graduate students' current practices for writing a mixed methods research study abstract," *International Journal of Multiple Research Approaches*, vol. 12, 2020.
- [17] B. Rienties, "Critical reflections and moving forward," in *Mixed Methods Social Network Analysis: Theories and Methodologies in Learning and Education*, 2019.
- [18] B. Geisinger and D. Raman, *Why They Leave: Understanding Student Attrition from Engineering Majors*, 2013.
- [19] L. Salas-Morera, A. Molina, J. Olmedilla, L. García-Hernández, and J. Romero, "Factors affecting engineering students dropout: A case study," *International Journal of Engineering Education*, vol. 35, pp. 156–167, 2019.
- [20] O. Viberg, M. Hatakka, O. Bälter, and A. Mavroudi, "The current landscape of learning analytics in higher education," *Computers in Human Behavior*, vol. 89, pp. 98–110, 2018.
- [21] I. Hilliger, C. Aguirre, C. Miranda, S. Celis, and M. Pérez-Sanagustín, "Design of a curriculum analytics tool to support continuous improvement processes in higher education," in *Proc. 10th Int. Conf. Learning Analytics and Knowledge*, 2020, pp. 181–186.
- [22] C. Pinnell, G. Paulmani, and V. Kumar, "Curricular and learning analytics: A big data perspective," in *Big Data and Learning Analytics in Higher Education*, 2017, pp. 125–145.
- [23] S. E. Schellpfeffer, "An introduction to curricular analytics: Research and applications for curriculum assessment and review," *Intersection: A Journal at the Intersection of Assessment and Learning*, vol. 6, no. 2, pp. 128–138, 2025.
- [24] S. Toraman and V. Clark, "Reflections about intersecting mixed methods research with social network analysis," in *Mixed Methods Social Network Analysis*, 2019, pp. 175–188.
- [25] A. Onwuegbuzie, "The PRICE of mixed methods social network analysis: Toward an ethical process for MMSNA," in *Mixed Methods Social Network Analysis*, 2019, pp. 245–262.