

Procedures and Motivations for Using Social Network Analysis in Higher Education Research in Scientific Fields: A Literature Review^{+,*}

*Bruna Schons Ribeiro*¹

Ph.D Student – Graduate Program in Physics Education

Federal University of Rio Grande do Sul

Porto Alegre – RS

*Leonardo Albuquerque Heidemann*¹

*Tobias Espinosa*¹

Federal University of Rio Grande do Sul

Porto Alegre – RS

Abstract

Humans are social beings, and social interactions play a crucial role in various domains, including education. Accordingly, this literature review examines how and for what purposes Social Network Analysis (SNA) has been employed in research on university student integration in STEM (Science, Technology, Engineering and Mathematics) academic environments. SNA stands out by focusing on relationships between actors rather than on individuals in isolation. Based on 52 studies, the following conclusions are drawn: (i) the use of SNA in this research field is relatively recent and still developing; (ii) SNA is a versatile methodology, allowing for the investigation of diverse research questions through a variety of data collection and analysis techniques; (iii) the lack of theoretical frameworks is a recurring limitation that, if addressed, could strengthen the conclusions of the studies; (iv) contextual variables significantly influence research findings, making it advisable for each institution to examine its own reality before adopting generalized actions.

Keywords: *Literature Review; Social Network Analysis; Higher Education; STEM; Student Interactions.*

⁺ Procedimentos e Motivações para a Utilização de Análise de Redes Sociais na Pesquisa em Ensino Superior em Áreas Científicas: Uma Revisão da Literatura

^{*} Received: May 2, 2025.

Accepted: November 5, 2025.

¹ E-mails: bruna.schons@ufrgs.br; tobiasesp@gmail.com; leonardo.h@ufrgs.br

I. Introduction

Humans are social beings. It is impossible to discuss the human species without considering how individuals relate to one another, form communities, and establish interactions. More than merely important, social relationships among people are regarded as basic needs by different psychological theories. Maslow (1943), for instance, proposed a hierarchy of basic human needs, in which the need for love, affection, and belongingness ranks just below physiological needs - such as eating and breathing - and those for safety and security. Deci and Ryan (1985), in their theory of motivation, identified relatedness as one of the three basic psychological needs essential to human beings, alongside autonomy and competence. In short, the need to establish interpersonal relationships has been a recurrent theme in motivational psychology, based on the understanding that human development cannot take place in isolation.

Interactions among individuals are fundamental in various spheres of human life, from the most evident ones, such as romantic, familial, or friendship relationships, to the more subtle ones, established in the workplace, school, or university. Personal development is tied to the construction of relationships among people who share the same environment (Osher *et al.*, 2021). This logic also applies to educational settings: for multiple reasons, students' integration into school or university environments appears to be crucial for achieving positive outcomes, including performance (Williams *et al.*, 2017; Williams *et al.*, 2019), persistence (Goertzen; Brewe; Kramer, 2013; Zwolak *et al.*, 2017), interest (Dou *et al.*, 2018), and self-efficacy (Zander *et al.*, 2018; Dou; Brewe, 2014).

Interactions among individuals may vary in many aspects. In educational contexts, for example, students may interact on an academic or social dimension; they may relate to a small or large number of peers; their interactions may be more or less frequent, meaningful, or long-lasting; and they may connect with people of diverse backgrounds or with a single specific profile. How might these and other variables affect the relationship between social integration and positive educational outcomes? Is there a consistent pattern in the relationships among these variables? In other words, do social interactions and their consequences manifest similarly across contexts, allowing institutional actions to be planned and implemented solely based on existing literature, or must each specific case be studied in depth so that interventions are appropriately tailored to local contexts?

One way to understand how different aspects of interpersonal interactions may lead to more positive educational outcomes is through Social Network Analysis (SNA). This methodology is particularly well-suited for such investigations because, in SNA, the unit of analysis is not the individual per se, but the entire system composed of actors and the connections among them (Wasserman; Faust, 1994). Whereas other methodologies might underestimate the influence of one element on another, it is precisely this relational structure that SNA enables us to examine.

The centrality of social interactions in education is supported by various psychological and sociological theories, which reinforces the relevance of SNA in this context. Across multiple theoretical traditions, relationships among individuals are conceived as constitutive elements of human development and social organization. This is evident in Erik Erikson's Psychosocial Development Theory (Erikson, 1963), Lev Vygotsky's Sociocultural Theory (Vygotsky, 1962; Vygotsky, 1978), and George Homans's Social Exchange Theory (Homans, 1974), as well as in sociological approaches such as George Herbert Mead's and Herbert Blumer's Symbolic Interactionism (Blumer, 1986), Social Role Theory (Linton, 1936; Linton, 1945; Goffman, 1959), and Anthony Giddens's Structuration Theory (Giddens, 1984). Aligned with these perspectives, SNA allows for the empirical representation and examination of the structures of interaction that these theories highlight as fundamental. In the educational field, this approach also resonates with Albert Bandura's Social Cognitive Theory (Bandura, 1986), James Wertsch's sociocultural approach (Wertsch, 1988; Wertsch, 1991), and Etienne Wenger's concept of communities of practice (Wenger, 1999), all of which emphasize the role of social relationships in learning and the formation of academic identities.

With this in mind, the focus of this literature review is to investigate how and for what purposes the methodology of Social Network Analysis has been employed in research on the integration of university students in academic environments within STEM fields. Since students' integration into university life directly affects their intention to persist (Zwolak; Zwolak; Brewe, 2018; Huerta-Manzanilla; Ohland; Peniche-Vera, 2021), and as the issue of student attrition and retention has gained prominence in educational research, we chose to explore this aspect in greater depth. This focus guided our selection of search terms and the studies included in the review.

The following sections present the methodology used for searching and selecting the analyzed papers, the results of the study, and finally, a discussion of these findings.

II. Paper Selection Methodology

This literature review has the characteristics of an integrative review (Botelho; Cunha; Macedo, 2011), as it seeks to analyze and synthesize existing knowledge from previous studies, generating new insights from their results. The review was conducted using papers selected from three databases: Scopus, Portal de Periódicos da CAPES, and Google Scholar. The search was carried out in August 2024, with no time restriction on publication dates. The following descriptors were used: (*"social integration" OR "academic integration" OR "university persistence" OR "student persistence" OR persistence OR dropout OR "chemistry education" OR "physics education" OR "biology education" OR "mathematics education"*) AND *"social network analysis"*.

We identified a total of 199 studies in Scopus, 1,557 in Portal de Periódicos da CAPES, and 39,000 in Google Scholar. In the case of Google Scholar, due to the large number of results, we selected the first 250 texts listed, ordered by relevance according to the platform's search

algorithm. We acknowledge that Google Scholar's "relevance" criterion is not fully transparent, as the system does not explicitly disclose the factors considered or their respective weights. Nevertheless, we chose to use this ordering method, as it is understood to consider aspects such as the match between the search terms and the title and content of the texts, the number of citations received, and the reputation of the authors and journals. Furthermore, this criterion was considered more appropriate than ordering by date, given that no temporal restriction was applied. In total, we initially selected 2,006 studies. After this first stage:

1. We excluded duplicates and papers not written in Portuguese, English, or Spanish;
2. We excluded, based on title screening, papers that were out of scope, such as those in which:
 - a. the term "social networks" referred to "social media" rather than the methodology itself;
 - b. SNA was applied in non-educational contexts;
 - c. the study was conducted with animals.
3. We excluded, based on abstract screening, papers that:
 - a. were books, theses, dissertations, undergraduate papers, or abstracts, since we limited our analysis to peer-reviewed journal and conference papers;
 - b. did not involve empirical data collection;
 - c. were literature reviews;
 - d. were conducted in K-12 education, as our focus was on higher education;
 - e. explored networks in which the nodes were not students;
 - f. explored only online interactions among students;
 - g. were conducted with students outside STEM fields or did not specify the students' field of study.

Following these procedures, which were carried out by the first author, 57 papers were selected for full reading. Of these, 5 were later excluded during the reading process. Therefore, our final analysis was based on the 52 papers listed in Appendix A.

During the review of the 52 selected papers, we used a structured table with guiding questions, in which relevant information from each study was systematically recorded. After completing this stage, we conducted a thematic categorization of the responses to these guiding questions. The analysis led to the definition of categories constructed inductively, based on the recurrence of conceptual patterns and the relevance of specific aspects to the review's objectives. This analytical process enabled us to organize and synthesize the data, particularly by grouping the categories related to the "objectives" and "results" of the studies, resulting in the themes presented in Section III.3.

III. Analysis of the Selected Literature

With the general goal of investigating how and for what purposes the methodology of Social Network Analysis has been used in research on the integration of university students in academic environments within STEM fields, we analyzed the 52 selected papers to address three research questions: (i) What is the profile of the academic production that employs SNA to study interactions among university students in academic STEM fields? (ii) How are studies that use SNA to investigate interactions among university students in academic STEM fields conducted? (iii) What are the main themes investigated by studies that apply SNA to examine interactions among university students in academic STEM fields? In this section, we discuss each of these questions in detail.

III.1 What is the profile of the academic production that employs SNA to study interactions among university students in academic STEM fields?

We found that the use of Social Network Analysis to study interactions among university students in STEM fields is still at an early stage. Among the 52 papers selected in this review, the earliest was published in 2010 (Brewer; Kramer; O'Brien, 2010). A noticeable increase in publications can be observed from 2017 onward, as shown in Fig. 1, although there is a smaller number in 2021, 2023, and 2024. It is not possible to determine with precision the reasons for this decrease; however, one hypothesis is that this research area may have been affected by the COVID-19 pandemic, which limited in-person instruction and, consequently, studies focusing on face-to-face interactions, particularly since one of our exclusion criteria was the analysis of exclusively virtual interactions.

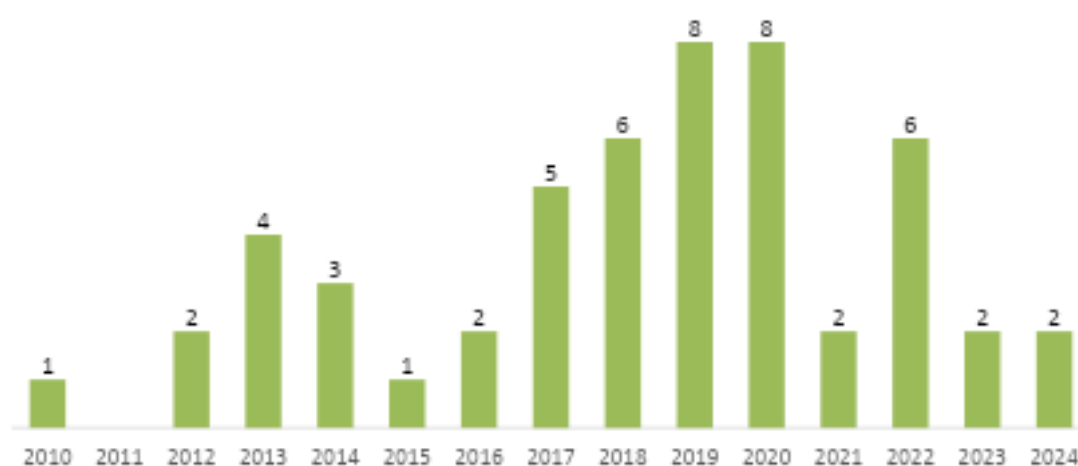


Fig. 1 – Histogram of studies included in the review by year of publication.

These data indicate that research on social interactions among STEM students through the lens of SNA is still developing and consolidating, leaving several aspects yet to be explored and room for further expansion of this research area. We also found that all selected papers

were written in English, even though texts in Portuguese and Spanish had been included in the initial selection. Although the United States accounts for a significantly higher number of studies (35 out of 52), researches conducted in other countries, such as Chile (Pulgar; Rios; Candia, 2019; Pulgar; Candia; Leonardi, 2020) and Germany (Zander *et al.*, 2018; Powazny; Kauffeld, 2021), were also published in English.

Even though the search terms were chosen to encompass all areas of the natural sciences (Physics, Chemistry, and Biology) and Mathematics, a large portion of the analyzed studies were developed in the context of Physics courses (27 out of 52). Other studies were conducted outside the classroom, including: (i) study and community spaces (Brewer; Kramer; Sawtelle, 2012); (ii) summer programs (Salzman *et al.*, 2020; Hass *et al.*, 2018; Pomian *et al.*, 2017); (iii) laboratory classes (Han; Oh; Kang, 2022); (iv) extracurricular research or innovation projects (Sonnenberg-Klein; Abler; Coyle, 2018); and (v) university databases containing demographic and enrollment data (Huerta-Manzanilla; Ohland; Long, 2013). These diverse contexts are important for characterizing interactions among students beyond the classroom, as relationships are not confined to formal academic spaces and may also play a key role in fostering students' personal, social, and academic development.

A final general characteristic of the analyzed papers is the diversity of theoretical frameworks and disciplinary perspectives that underpin their development. Among the most frequently used frameworks is Albert Bandura's Social Cognitive Theory - particularly its concept of self-efficacy - which is employed in five studies (Dou; Brewer, 2014; Dou *et al.*, 2018; Dou *et al.*, 2016; Olivares *et al.*, 2019; Zander *et al.*, 2018). Models of student attrition and persistence - especially those of Vincent Tinto - are used in six studies (Forsman; Moll; Linder, 2014; Huerta-Manzanilla; Ohland; Long, 2013; Williams *et al.*, 2017; Williams *et al.*, 2019; Zwolak; Brewer, 2015; Zwolak *et al.*, 2017). It is noteworthy that a considerable number of papers (25 out of 52) do not explicitly state a theoretical framework. While the identification of correlations is in itself an interesting outcome, the absence of a theoretical grounding for analysis can limit the interpretation of findings and the formulation of well-founded conclusions directed toward specific research problems.

III.2 How are studies that use SNA to investigate interactions among university students in academic STEM fields conducted?

To study interactions among individuals, it is necessary to capture the occurrence of such interactions. Frequently, however, obtaining information about events that may happen at any time, in any place, and beyond the researchers' direct observation is complex and challenging. For this reason, several strategies are employed to make the collection of such data feasible.

Questionnaires stand out as the primary data collection instrument. Of the 52 analyzed papers, 41 used some type of questionnaire to investigate with whom students had interacted. Moreover, in 30 of these 41 studies, the instrument was administered at least twice, either to

assess temporal changes in the network or as a methodology for pre- and post-test comparison. In general terms, these questionnaires included questions such as: “*Please choose from the list of people that are enrolled in your physics class the names of any other student with whom you had a meaningful interaction in class during the past week, even if you were not the main person speaking.*” (Traxler *et al.*, 2020, p. 6); “*Who do you work with to learn physics?*” (Brewer; Kramer; O’Brien, 2010, p. 86); and “*Which of your fellow students would you consider a friend?*” (Boda *et al.*, 2020, p. 9).

However, the goal of such studies is not always to identify the students who most frequently interact with their peers (the next section will address research objectives); in these cases, the questions posed to participants differ. For example, in Grunspan *et al.* (2016), the researchers investigated the trust students had in their peers, and thus the questionnaire asked them to name classmates they felt were “*strong in their understanding of classroom material*” (p. 2). A similar question was asked by Sundstrom and Kageorge (2024), who sought to identify students with the highest peer recognition: “*asking students to nominate peers they felt were strong in their physics course*” (p. 4).

It is important to note that, due to the inherent characteristics of this instrument, participants are required to recall their past interactions, meaning that this method entails the loss of information that cannot be retrieved from memory. Furthermore, students who do not respond to the questionnaire also increase missing data. Nonetheless, studies such as Smith and Moody (2013) demonstrate that the networks constructed remain representative of reality even with incomplete information. In other words, although questionnaires often do not allow for full identification of interaction data, SNA methodology still produces meaningful results. This can be considered one of the most accessible ways to collect data for constructing social networks and, for that reason, was chosen in nearly 80% of the analyzed studies.

However, questionnaires are not the only method used to collect information on student interactions. Some studies have also employed classroom observations (Boda *et al.*, 2020; Brown, 2019; Commeford; Brewer; Traxler, 2021) and video recordings (Goertzen; Brewer; Kramer, 2013; Hass *et al.*, 2018; Pomian *et al.*, 2017; Sundstrom *et al.*, 2022; Walsh; Lushaliev; Holmes, 2020) for data collection. Although these methods provide a more accurate portrayal of interactions than questionnaires, the volume of data imposes stricter spatial and temporal constraints on data collection. While questionnaires can request that participants report interactions that occurred over the previous weeks, observation and video analysis make this nearly unfeasible due to the large amount of data to be processed. Researchers must therefore evaluate their aims and study context to determine which data collection instrument is most appropriate.

In addition to these traditional methods, some studies (15 out of 52) collected information from course databases, institutional records, or even national databases. For instance, Ramsey *et al.* (2023) examined the implications of participants taking multiple courses with the same peers, where network connections did not represent direct interactions

but rather co-enrollment in the same course. Finally, interviews (Benbow; Lee, 2022; Berhan *et al.*, 2019; Brown, 2019; Goertzen; Brewe; Kramer, 2013), instructors' perceptions (Grunspan *et al.*, 2016; Sundstrom; Kageorge, 2024), and classroom activities (Fire *et al.*, 2012; Olivares *et al.*, 2019; Pulgar; Candia; Leonardi, 2020; Williams *et al.*, 2015) were also used as data sources. Thus, although questionnaires are preferred, there are multiple possibilities for data collection in SNA studies, depending on each study's objectives and feasibility.

Following data collection, the next step is naturally data analysis. Since SNA is primarily a quantitative methodology, it often requires software to calculate network metrics. The R programming language - particularly the *igraph* package - was the most commonly used tool, appearing in 24 of the 52 studies. Python (4 of 52) and the softwares *Ucinet* (7 of 52), *Pajek* (2 of 52), *Gephi* (2 of 52), and *Negopy* (1 of 52) were also employed. There is, therefore, a clear preference for R, likely due to its versatility and the wide range of available packages that support network analysis.

However, some studies do not rely on network metrics. In certain cases, researchers simply counted the number of interactions of each network member - that is, the degree, or in the case of directed networks, the indegree and outdegree - making specialized software unnecessary. This was the case in Benbow and Lee (2022), Pomian *et al.* (2017), and Ramsey *et al.* (2023). Researchers may also analyze network characteristics descriptively through graphical representations, as seen in Salzman *et al.* (2020). Other studies presented the mathematical equations of the metrics used directly in the text, without specifying the software or programming language used for calculation, as in Huerta-Manzanilla, Ohland, and Peniche-Vera (2021); Sundstrom *et al.* (2022); Sundstrom and Kageorge (2024); and Walsh, Kushaliev, and Holmes (2020). Despite the value of these alternative analyses, employing social network metrics enables the identification of structural features that go beyond purely visual interpretation.

SNA encompasses a wide range of measures that assess different characteristics of both entire networks and their components. The papers analyzed in this review used a broad variety of metrics. Some measures stood out for their frequent use, such as degree measures (degree, indegree, outdegree, and their weighted versions), which appeared in 38 of the 52 papers. Various centrality measures (degree, closeness, harmonic, betweenness, eigenvector, Bonacich's) were used in 18 studies, and density was also examined in 18 studies. Individual measures such as degree and centrality are commonly used to investigate relationships with individual characteristics, including social (Grunspan *et al.*, 2016; Brown, 2019) and psychological aspects (Dou *et al.*, 2016; Dou; Zwolak, 2019; Turetsky *et al.*, 2020), performance (Pulgar; Candia; Leonardi, 2020; Williams *et al.*, 2015), and persistence (Zwolak *et al.*, 2017; Zwolak; Brewe, 2015). Density, in turn, is more frequently used in studies analyzing networks holistically, such as those comparing active and traditional teaching methodologies (Brewe; Kramer; O'Brien, 2010; Sundstrom *et al.*, 2022) or evaluating participation in communities and organizations (Berhan *et al.*, 2019).

In summary, trends were identified in how SNA studies investigate interactions among university students in STEM fields: (i) questionnaires as the main data collection instrument; (ii) the R programming language as the preferred tool for metrics calculation; and (iii) degree, centrality, and density measures as the most recurrent metrics for characterizing students' social networks. Despite these prevailing characteristics, there is substantial variation in instruments, software, and metrics, allowing for investigations with diverse objectives that contribute to answering a wide range of research questions.

III.3 What are the main themes investigated by studies that apply SNA to examine interactions among university students in academic STEM fields?

As described in the previous section, regarding methodologies used for data collection and analysis, there is also a wide variety of objectives and results that can be achieved in research on student interactions using SNA. Table 1 summarizes the information obtained.

Table 1 – General themes investigated in the analyzed studies, highlighting research objectives and findings.

Themes	Objectives	Results
Differences in network structures and characteristics over time and across different environments and contexts	Analyze learning interactions outside the classroom.	– Differences emerge between social and academic networks, within and outside the classroom, and between informal and academic interactions.
	Assess whether taking courses with the same peers influences academic success.	– Student relationships tend to weaken with the progression of years. – The network structure becomes stable as the semester progresses.
	Evaluate differences across types of networks (academic and social).	– Students interact more frequently with peers from their own work groups than with those from other groups. – Extracurricular communities/organizations are important for fostering interactions. – Connections formed between students are not random; they are influenced by contextual factors. – Students have more academic interactions with peers from the same academic year and the same major. – The quality of interactions is more important than the quantity.
Relationships between integration, social characteristics, and psychological constructs	Evaluate the relationship between students' integration and psychological constructs, success markers, interest in	– There are correlations between integration/network metrics and psychological constructs (e.g., self-efficacy, growth mindset, self-reliance/self-sufficiency, sense of belonging, anxiety, interest in physics/science, and values

	physics.	affirmation). – Differences in network metrics are observed based on gender and race/ethnicity. – Persistence is related to the approval/disapproval of significant others – Peer recognition is dependent on outspokenness.
	Explore the influence of social characteristics (e.g., race and gender) on integration.	
Relationships between integration, academic performance, and persistence	Investigate the relationship between integration and academic performance.	– Persistence is related to performance. – Persistence is related to integration/network metrics.
	the influence of student interactions on dropout / attrition, persistence, and retention.	– Integration/network metrics are positively associated with academic performance. – There is a relationship between a student's grade and the grades of their friends.
Impact of pedagogical methodologies, interventions, and participation on student integration	Highlight differences in students' integration as a function of the teaching methodology used in the classroom.	– Helping peers with assignments is related to performance. – Non-traditional courses / active learning methodologies / open-ended problems resulted in greater integration/interaction.
	Analyze factors that influence the formation and evolution of networks.	– Participation in activities influences integration. – Performance is distinctly influenced by integration in lecture-based courses and laboratory settings.
	Impact of interventions on students' networks.	

III.3.1 Differences in network structures and characteristics over time and across different environments and contexts

This category groups studies that investigated student interactions in spaces beyond the classroom, the impact of time on the evolution of networks, and structural characteristics of those networks.

Different spaces within the university may foster the development and strengthening of relationships among students in ways that traditional classrooms alone may not provide. A clear example found in this review is the case of summer bridge programs, examined in the studies of Boda *et al.* (2020), Hass *et al.* (2018), Pomian *et al.* (2017), and Salzman *et al.* (2020). These programs were designed as support mechanisms for first-year students, who participate in university activities before beginning their first academic semester. For instance, in Salzman *et al.* (2020), although the authors identified that the relationships formed during the summer program weakened over subsequent semesters, first-year students who participated in the program were found to be more connected to their peers than those who did not. This indicates that such early connections among students may not last indefinitely, but they are important in helping newcomers adapt to the university environment and feel more welcomed.

Other study environments within universities, such as a Physics Learning Center (Brewer; Kramer; Sawtelle, 2012) and laboratories classes (Han; Oh; Kang, 2022), were also

found to be relevant in producing positive outcomes for students. In the case of Brewe, Kramer, and Sawtelle (2012), the authors argue that, to promote student persistence, *“physics departments could take active steps to provide pathways and access to participation in a learning community”* (p. 8). Similarly, Han, Oh, and Kang (2022) found results indicating the importance of knowledge sharing for students’ learning performance. Thus, although students may develop group-study skills - and benefit from them - within a traditional classroom, providing such experiences in other environments where interactions are central to learning seems to be an important complement to classroom-based relationships.

This category also includes studies that assessed differences between what we refer to as academic and social student interactions, that is, interactions that are and are not, respectively, formally related to academic matters at the university (Forsman; Moll; Linder, 2014; Pomian *et al.*, 2017; Stadtfeld *et al.*, 2019). All three studies showed differences between academic and social networks; in other words, students do not interact with the same peers regarding academic and non-academic issues. Furthermore, positive academic outcomes, such as good grades or persistence, were associated not only with academic interaction networks but also with social ones. For this reason, Forsman, Moll, and Linder (2014) suggest that *“researchers, educators, and policy makers not only need to address critical aspects of the academic environment, but the same kind of research rigor needs to be used to address the social side of studying”* (p. 11).

III.3.2 Relationships between integration, social characteristics, and psychological constructs

This category includes studies that examine how interactions among students influence or are influenced by psychological constructs and social characteristics.

Learning - translated through performance - and persistence are frequently identified as positive outcomes of student interactions. The next category, which will be discussed later, addresses this in detail. However, several researchers have also focused on elements of the educational environment that may mediate this relationship, as well as contribute to greater well-being and motivation among students. This includes studies that investigate how academic interactions may impact various psychological constructs.

Among the constructs evaluated are: self-efficacy (Dou; Brewe, 2014; Dou *et al.*, 2016; Dou *et al.*, 2018; Zander *et al.*, 2019); growth mindset (Zander *et al.*, 2019); markers of student success such as attitudes about learning, ties within the physics classroom, and relationships in the physics learning community (Goertzen; Brewe; Kramer, 2013); sense of belonging (Benbow; Lee, 2022; Salzman *et al.*, 2020); peer trust (Grunspan *et al.*, 2016); anxiety levels (Dou; Zwolak, 2019); interest in physics and science in general (Dou *et al.*, 2018); and value affirmation (Turetsky *et al.*, 2020). Some of these constructs are elements of well-known psychological theories, such as Albert Bandura’s Social Cognitive Theory (Bandura, 1986), Carol Dweck’s Growth Mindset Theory (Dweck, 2007), and Claude Steele’s

Self-Affirmation Theory (Steele, 1988). Others are related to students' behaviors, attitudes, and perceptions of aspects of the academic environment.

Once again, this variety demonstrates how SNA is a versatile methodology for investigating student interactions and shows that these relationships have effects extending beyond performance. Seeking an education that is not limited to achievement, we gather evidence from different dimensions of academic life that are influenced by students' social connections.

However, not all students have equal opportunities to interact with their peers. For this reason, several studies have identified the influence of social characteristics - especially gender and race/ethnicity - on students' interaction patterns. Of the 52 studies analyzed, 19 examined the influence of at least one social characteristic on student interactions.

Several of these studies found no significant association between social characteristics and the analyzed network metrics, including Alcock *et al.* (2020), Brewe, Kramer, and Sawtelle (2012), Hass *et al.* (2018), Ramsey *et al.* (2023), Stadtfeld *et al.* (2019), Sundstrom and Kageorge (2024), Turetsky *et al.* (2020), Zwolak and Brewe (2015), Zwolak *et al.* (2017), and Zwolak, Zwolak, and Brewe (2018). This means that, in these contexts, there were no differences in student interactions based on gender, race/ethnicity, or socioeconomic status. The study by Hass *et al.* (2018), for instance, analyzed a group of deaf or hard of hearing students and found no interaction differences when compared with hearing students.

However, this is not the case for all studies. Some identified differences in interactions by gender (Brown, 2019; Grunspan *et al.*, 2016; Han; Oh; Kang, 2022; Jeffrey *et al.*, 2022; Reinholz, 2017; Simpfendoerfer *et al.*, 2024; Williams *et al.*, 2015), race/ethnicity (Berhan *et al.*, 2019; Reinholz, 2017; Salzman *et al.*, 2020), and socioeconomic status (Jeffrey *et al.*, 2022). Nevertheless, it is important to highlight that, contrary to what might be expected, underrepresented social groups do not always display fewer interactions in their networks. For example, in Reinholz (2017), the author found that *"out-of-class networks show that African American, Asian, and Hispanic students were the most connected"* (p. 532), but *"the highest degrees for being recognized as contributors were for Asian and White students which is consistent with racial narratives in the US"* (p. 532). Similarly, in Berhan *et al.* (2019) and Salzman *et al.* (2020), the authors did not find evidence that minority racial/ethnic groups interact less with peers, but rather that they emphasize the importance of representation within the university environment. In Salzman *et al.* (2020), networks exhibited high homophily, meaning that *"we see what appears to be distinct and separate networks of URM and Non-URM"* (p. 8). In Berhan *et al.* (2019), the authors identified that *"black engineering organizations [...] were of critical importance to the connectedness and sense of belonging of the students"* (p. 6), despite the fact that networks of Black engineering students at a historically Black university were denser than those at a predominantly White institution.

The same phenomenon can be observed regarding gender differences in some studies. In Jeffrey *et al.* (2022), Simpfendoerfer *et al.* (2024), and Williams *et al.* (2015), the authors

found that female students exhibited higher degree centrality than male students, indicating interactions with a larger number of peers. However, there are also studies in which male students occupied more favorable positions in the investigated social networks. In Reinholz (2017), for example, male students exhibited higher degree centrality than female students in three of the four analyzed networks. In Han, Oh, and Kang (2022), the authors identified high gender homophily in networks, meaning that male students interacted more with other males, and female students more with other females.

Two studies stand out for presenting deeper findings on this topic. In Brown (2019), the author identified that men were more central within groups, interacting primarily with other men, whereas women occupied more peripheral positions and tended to play bridging roles. Women had considerably higher betweenness centrality values, meaning they were responsible for connecting different groups. In contrast, Grunspan *et al.* (2016), whose main objective was to investigate how gender influences students' trust in peers' biology knowledge, found that male students were consistently more often cited as being "*strong in their understanding of classroom material*" (p. 2) than female students across all surveys. Male students also showed a significant bias toward nominating other males. The authors reached a regrettable yet unsurprising conclusion: "*females achieving high grades and outspoken status never gain the same celebrity status as their male counterparts. It appears that being male is a prerequisite for students to achieve celebrity status within these classrooms*" (p. 9).

These results suggest that assuming women and underrepresented groups necessarily display lower interaction measures with their peers is inaccurate. However, it is also impossible to ignore that such differences occur in some contexts. Therefore, it is advisable for each institution to examine its own reality to identify potential differences and segregation within its social fabric. Making these disparities visible is essential for directing actions toward specific groups that may require greater support from faculty and institutions to create a more welcoming academic environment for everyone equally.

III.3.3 Relationships between integration, academic performance, and persistence

This category includes studies investigating how interactions among students can affect performance on assessments and persistence in their studies. This is the most frequently explored topic when using SNA to analyze interactions among university students in STEM fields. Among the 52 studies analyzed, 16 examined relationships between integration and performance, while 11 investigated how interactions influence dropout, persistence, or retention.

Of the 16 studies that examined the relationship between student integration and performance, 13 (Bruun; Brewe, 2013; Crespo; Antunes, 2015; Crossette; Carr; Wilcox, 2023; Han; Oh; Kang, 2022; Ramsey *et al.*, 2023; Reinholz, 2017; Simpfendoerfer *et al.*, 2024; Stadtfeld *et al.*, 2019; Vargas *et al.*, 2018; Williams *et al.*, 2015; Williams *et al.*, 2017; Williams *et al.*, 2019; Yang *et al.*, 2014) found positive correlations. In general, this means that students

who interact more with their peers tend to achieve better academic performance. These conclusions were reached by associating one or more measures of degree and/or centrality with grades in a specific test or assignment, or, more commonly, with the final course grade. The remaining three studies did not focus directly on these relationships, instead examining: the association between a student's final grade and those of their friends, which was statistically significant (Fire *et al.*, 2012); the relationship between peer interactions and study habits, and later between study habits and performance, which was not supported by the data (Alcock *et al.*, 2020); and a negative correlation between network metrics and grades (Pulgar; Candia; Leonardi, 2020). Although this last finding appears to contradict the majority, it requires closer attention to network construction. In Pulgar, Candia, and Leonardi (2020), the authors built a collaboration network among students by asking whom they sought out for help with problem-solving. Students with higher grades tended to have lower outdegree values because they cited fewer peers (sought less help), while students with lower grades had higher outdegree values because they cited more peers (sought more help).

Regarding persistence, dropout, or retention, of the 11 studies that investigated the impact of interactions on academic continuity, 9 (Assis *et al.*, 2022; Huerta-Manzanilla; Ohland; Long, 2013; Huerta-Manzanilla; Ohland; Peniche-Vera, 2021; Powazny; Kauffeld, 2021; Ramsey *et al.*, 2023; Turetsky *et al.*, 2020; Zwolak; Brewe, 2015; Zwolak *et al.*, 2017; Zwolak; Zwolak; Brewe, 2018) found positive correlations. Additionally, one study that did not explicitly aim to relate integration and persistence identified, through interviews, the importance of feeling part of a community to reduce the likelihood of dropping a course or leaving the program altogether (Goertzen; Brewe; Kramer, 2013). Ramsey *et al.* (2023), Turetsky *et al.* (2020), Zwolak and Brewe (2015), Zwolak *et al.* (2017), and Zwolak, Zwolak, and Brewe (2018) found positive associations between measures of degree and/or centrality and persistence. Meanwhile, Huerta-Manzanilla, Ohland, and Long (2013) linked reciprocity between dyads to persistence, and Huerta-Manzanilla, Ohland, and Peniche-Vera (2021) found that denser networks favored persistence. Conversely, two studies explored factors that could motivate dropout: Assis *et al.* (2022) identified that network isolation increased dropout probability, while Powazny and Kauffeld (2021) showed that the disapproval of influential others impacted students' dropout intention.

As with performance, student integration, as measured by interactions with peers, proves to be fundamental for persistence throughout the academic trajectory. Symmetrically, when students are unable to build and maintain peer connections, or when such connections are negative, the likelihood of withdrawal increases. Thus, social interactions are not only essential for academic achievement in a course or assessment but also play a decisive role in shaping a successful university journey.

III.3.4 Impact of pedagogical methodologies, interventions, and participation on student integration

This category encompasses studies aimed at identifying how student interactions are influenced by classroom methodologies and interventions implemented by instructors or institutions. It also includes analyses of factors affecting the formation or evolution of networks.

Among the 52 analyzed papers, 9 evaluated differences in student integration depending on classroom methodology or course type. Brewe, Kramer, and O'Brien (2010) and Yang *et al.* (2014) found that, in classes using active methodologies, all students were part of the social network, whereas in lecture-based classes, many students were isolated and excluded from the network. They also observed that, in classes with active methodologies, the number of connections among students increased throughout the semester, whereas no such growth occurred in lecture-based classes. Commeford, Brewe, and Traxler (2021) and Traxler *et al.* (2020) analyzed various active learning methodologies and concluded that all of them increased student interactions. However, Modeling Instruction stood out as the methodology producing the most significant increase in connections. Similarly, Reinholz (2017) and Sundstrom *et al.* (2022) also reported more student connections in classes with active methodologies compared to traditional ones. Pulgar, Rios, and Candia (2019) and Pulgar, Candia, and Leonardi (2020) examined the implementation of open-ended problem-solving activities and found evidence that this methodology fosters interaction among students, as it requires creativity and information sharing (Pulgar; Candia; Leonardi, 2020). Finally, Simpfendoerfer *et al.* (2024) did not assess differences in the number of interactions but rather the reasons for interacting in lecture and laboratory courses. They found that, in laboratories, most interactions were motivated by small-group work, while in lecture courses, they were primarily driven by homework assignments. In summary, there is evidence that active methodologies promote student connections more effectively than traditional ones. Considering the benefits associated with a greater number of interactions, as discussed in earlier sections, these findings reinforce the importance of adopting active learning methodologies in educational contexts.

Beyond instructional methods, some studies also examined the influence of other actions or interventions initiated by instructors or institutions. These interventions included: a learning community (Jeffrey *et al.*, 2022); a software to suggest requesting/offering help among peers (Olivares *et al.*, 2019); and a value-affirmation activity (Turetsky *et al.*, 2020). In all three studies, students who participated in the interventions interacted more with their peers than those who did not. These findings provide insights for educators and researchers seeking strategies to increase student interaction.

Other studies identified several additional factors that influenced the formation and/or evolution of student networks. In addition to aspects previously mentioned, such as social characteristics, classroom methodologies, and participation in extracurricular environments, references were found regarding the impact of classroom physical layout (Commeford; Brewe; Traxler, 2021; Wolf *et al.*, 2022); group formation and choice of partners (Alcock *et al.*, 2020;

Boda *et al.*, 2020; Fire *et al.*, 2012; Han; Oh; Kang, 2022; Walsh; Kushaliev; Holmes, 2020; Wells, 2019; Wolf *et al.*, 2022); course stage (Alcock *et al.*, 2020; Assis *et al.*, 2022; Han; Oh; Kang, 2022; Salzman *et al.*, 2020); and participation in activities (Brewer; Kramer; Sawtelle, 2012; Sundstrom; Kageorge, 2024). These results indicate that promoting or hindering interactions in the classroom depends on multiple factors, some of which are quite simple. Structuring classrooms so that students sit together and work collaboratively, organizing groups so that students interact with different peers in each task, and encouraging participation can foster relationships that might not occur spontaneously. Conversely, in classrooms arranged in rows, where students primarily complete individual assignments and assessments, and repeatedly work with the same peers while being discouraged from active participation, building a dense and diverse network becomes highly unlikely.

Therefore, this category shows that student interactions are significantly and diversely affected by the actions of instructors and institutions. This is positive, as it demonstrates that actions can be designed and implemented to foster new connections and strengthen existing ones. However, it is possible, and even likely, that some instructors and institutions are unaware of the importance of student relationships for academic success and of the power they hold to create such favorable conditions. Thus, this review, supported by multiple studies, suggests that promoting student interactions can be achieved through simple or complex actions, both of which yield highly positive outcomes across various aspects of students' academic trajectories.

III.3.5 Synthesis

The findings of this review demonstrate that student integration occupies a central role in students' university trajectories. It both influences and is influenced by network structures, social characteristics, and psychological constructs, as well as by academic performance, persistence, and the pedagogical methodologies and interventions adopted by instructors. This "network" of influences can be represented in Fig. 2.

These four axes articulate dynamically, establishing relationships not only with integration but also among themselves. Pedagogical practices shape opportunities for interaction and participation; the configuration of networks and the experiences of belonging and support influence the development of relevant psychological constructs; these factors, in turn, besides being capable of modifying the student's position within the network, also impact engagement, performance, and persistence; and academic success tends to feed back into integration and network participation. These interconnections reinforce the understanding that social, psychological, pedagogical, and academic processes do not operate in isolation. Thus, as illustrated in Fig. 2, integration emerges as the articulating element of an interdependent system in which structural, subjective, and institutional factors mutually influence one another throughout the university trajectory.

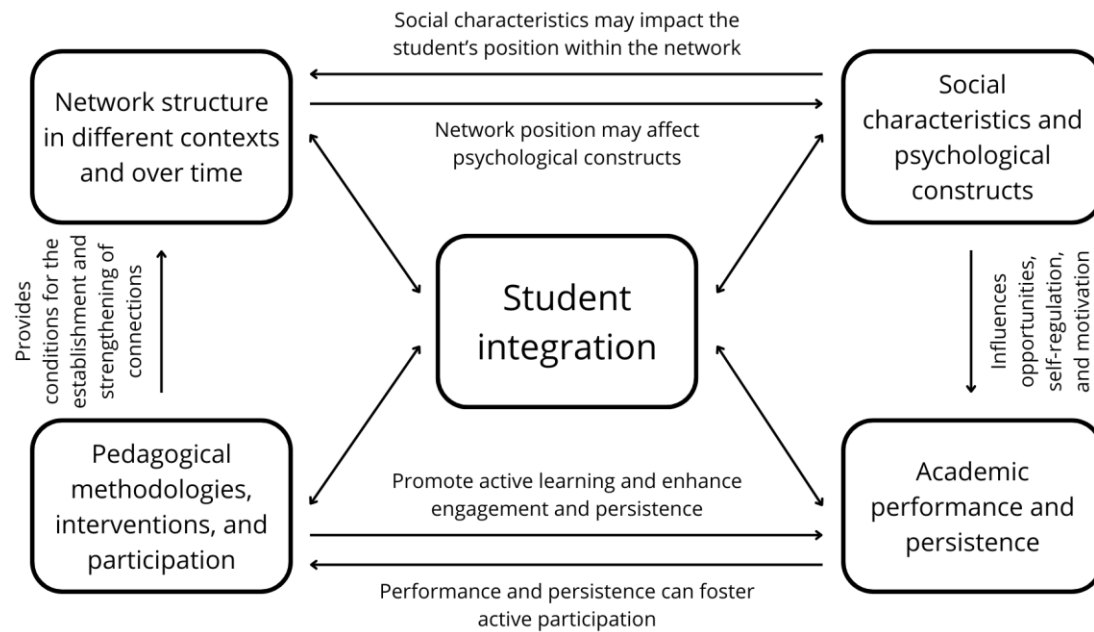


Fig. 2 – Network of relationships between student integration and the four themes emerging from the analysis.

IV. Final Considerations

In this literature review, we investigated how and for what purposes the methodology of Social Network Analysis (SNA) has been employed in research on the integration of university students in academic environments within STEM fields. After selecting and analyzing 52 papers, we addressed the three research questions: (i) What is the profile of the academic production that employs SNA to study interactions among university students in academic STEM fields? (ii) How are studies that use SNA to investigate interactions among university students in academic STEM fields conducted? (iii) What are the main themes investigated by studies that apply SNA to examine interactions among university students in academic STEM fields?

Regarding the profile of the academic production, we identified that SNA is still a relatively recent research methodology in STEM education, with the earliest paper published in 2010, followed by a noticeable increase in publications in 2017. The vast majority of studies were conducted in the United States, and all texts were written in English, even when the studies took place in countries where English is not the official language. More than half of the research was carried out in physics courses, although there are also studies in chemistry, biology, mathematics, programming, and outside the formal classroom setting. Finally, it is worth noting the absence of a theoretical framework in almost half of the analyzed papers; among those that explicitly presented one, the most frequent choices were the Social Cognitive Theory and persistence/retention models.

Regarding data collection and analysis, the variety of methods employed is evident. Although there is a preference for using questionnaires as data collection instruments and the R programming language for data analysis, several other approaches exist. In addition to questionnaires, researchers used observations, video recordings, interviews, university database analyses, teachers' perceptions, and classroom activities. For data analysis, Python language and the softwares Ucinet, Pajek, Gephi, and Negopy were also used, as well as studies based on descriptive analyses and interaction counts. The most frequently used metrics were degree and centrality for individual measures, and density for global measures; however, there is also a wide variety of metrics employed, exposing different analytical possibilities. These results indicate that, despite the frequent use of questionnaires and R by researchers, SNA is a highly versatile methodology with multiple research potentials, which can be employed to address diverse research questions.

Finally, concerning the themes investigated, the versatility that SNA brings to research once again becomes evident. Although we condensed the themes into four categories for synthesis purposes, Table 1 demonstrates the diversity of research objectives and findings obtained through the use of SNA in investigations on student interactions in STEM fields. The four defined categories - (i) Differences in network structures and characteristics over time and across different environments and contexts; (ii) Relationships between integration, social characteristics, and psychological constructs; (iii) Relationships between integration, academic performance, and persistence; (iv) Impact of pedagogical methodologies, interventions, and participation on student integration – show that interactions both influence and are influenced by various factors, revealing a wide range of research possibilities and, consequently, implications for students' academic lives.

In summary, we conclude that the research objectives and questions, methods employed, and results obtained are quite diverse, indicating that SNA can be used to investigate multiple aspects of student interactions in university settings. Therefore, regardless of the specific relationships one intends to establish between personal connections, the use of Social Network Analysis can be a valuable approach.

A point worth highlighting in this review is the absence of a theoretical framework in a significant portion of the analyzed papers (25 out of 52). As stated in the introduction of this paper, several theories from fields such as Psychology, Sociology, and Education can serve as foundations to theoretically support analyses based on SNA metrics and statistics. Although numerous theories highlight social interactions as fundamental to different aspects of human life, they were rarely employed in the interpretation of data in studies on student interactions using SNA. The adoption of a theoretical framework that considers the relevance of interpersonal connections could contribute to the construction of more sophisticated conclusions that go beyond the mere identification of statistical correlations.

Another gap identified was the limited number of studies conducted outside the United States. Particularly when observing our own context, we found few studies carried out in Latin

America: only two in Chile (Pulgar; Rios; Candia, 2019; Pulgar; Candia; Leonardi, 2020) and one in Brazil (Assis *et al.*, 2022). This limitation may affect the generalizability of findings, given the contextual differences in higher education across countries. We also observed the near absence of studies that followed students for periods longer than a single course. Longitudinal studies investigating differences throughout the undergraduate years could provide valuable insights into how networks evolve as students progress through their programs.

An important aspect emerging from the analysis concerns the impact of social characteristics on student interactions. We expected to find more papers reporting differences in terms of race/ethnicity, gender, and socioeconomic status; however, as described in the previous section, among the studies that analyzed social characteristics, more than half (10 out of 19) found no differences in social interactions in terms of these variables. Additionally, among those that did find differences, there were cases in which groups that are usually underrepresented exhibited higher interaction metrics according to SNA.

This result leads to the conclusion that it is not possible to assume, *a priori*, that certain social groups will necessarily occupy peripheral positions within university or course networks. Nor is it possible to rely solely on the literature to make such claims, since network configurations are context-specific and may or may not be influenced by social characteristics, either positively or negatively. For this reason, the ideal scenario is for each institution to assess its own context individually, ensuring that the diagnosis of student networks is as accurate as possible for that environment, and that any actions planned based on such assessment are well aligned with local particularities rather than external assumptions.

In terms of dropout and persistence, Tinto (1993) had already emphasized that only institution-specific studies can provide a real understanding of the investigated context:

The point here is really quite simple, namely, that institutional rates of departure are necessarily a reflection of the particular attributes and circumstances of an institution. Though the sharing of a common attribute, such as four-year status and selectivity, may imply a commonality of circumstances, only institution-specific studies of departure can provide insight into the circumstances which lead to a given rate of departure from a particular institution (Tinto, 1993, p.22).

Likewise, we found no consistent evidence of differences for other aspects investigated in classroom settings; thus, while previous studies in the literature are important to “map the landscape”, only an in-depth study of one’s own context can provide specific and meaningful insights into the local environment. In this sense, we emphasize the importance of institutions interested in fostering student integration conducting their own studies to identify the specific characteristics of their student connection networks. This diagnostic process is the first step, allowing for the design and implementation of actions better targeted to the intended audience. Despite contextual particularities, some ideas may serve as inspiration: strategies to foster a sense of belonging among underrepresented students; collaborative spaces for developing study

groups; mentoring and welcoming programs for newcomers; the use of active learning methodologies that promote teamwork; and the creation of learning communities that allow students to take courses together, among others.

Among this study's limitations, we highlight the selection of papers through Google Scholar, which, by providing a large number of references, made it impossible to fully analyze all search results. Therefore, it was necessary to establish a cutoff point in the first stage of selection. It should also be noted that, although we used English descriptors in our search, this should not pose a problem since papers in other languages generally have their title and abstract translated into English. Nevertheless, we found few texts written in Portuguese and Spanish, and all papers in the final sample were in English.

As future perspectives, we suggest advancing research that explores student integration in different cultural, institutional, and disciplinary contexts, especially outside the U.S., thereby broadening the geographical and epistemological diversity of SNA studies in education. Longitudinal investigations that follow the evolution of networks throughout undergraduate programs may also offer deeper insights into the processes of formation, maintenance, and transformation of student connections. Moreover, combining SNA with qualitative approaches such as interviews, observations, or discourse analysis could enrich data interpretation, allowing researchers to understand not only how interactions occur but also why they are established and maintained. Finally, the development of studies guided by robust theoretical frameworks that articulate social, cognitive, and affective dimensions of academic life represents a promising path for consolidating SNA as a powerful and interdisciplinary methodology in research on student integration in STEM fields.

In summary, this review demonstrates that there are some common ways of conducting research in academic environments using SNA, an aspect that may be particularly useful for researchers new to this area. However, this is a highly versatile and comprehensive methodology that enables a wide range of investigations into interactions among actors. The contributions we consider most relevant to the field of STEM education research include encouraging the development of more theoretically grounded studies, whether on social interactions or the constructs being related to them, so that results and conclusions may become more sophisticated than mere statistical correlations. Additionally, we encourage institutions and researchers to conduct local studies, keeping the literature in mind but recognizing that interpersonal relationships and their influencing factors are context-dependent. Just as in astronomical observations, where increasing resolution requires narrowing the field of view, more focused investigations within specific institutions may enhance the precision with which we observe and understand a unique reality.

Acknowledgements

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001.

References

BANDURA, A. **Social Foundations of Thought and Action: A Social Cognitive Theory**. Hoboken: Prentice Hall, 1986. 640 p.

BLUMER, H. **Symbolic interactionism: Perspective and method**. Oakland: University of California Press, 1986. 224 p.

BOTELHO, L.; CUNHA, C.; MACEDO, M. O método da revisão integrativa nos estudos organizacionais. **Gestão e Sociedade**, v. 5, n. 11, p. 121-136, 2011.
<https://doi.org/10.21171/ges.v5i11.1220>

DECI, E. L.; RYAN, R. M. **Intrinsic motivation and self-determination in human behavior**. New York: Plenum Press, 1985. 372 p.

DWECK, C. S. **Mindset: The new psychology of success**. New York: Ballantine Books, 2007. 320 p.

ERIKSON, E. H. **Childhood and society**. New York: W. W. Norton, 1963. 445 p.

GIDDENS, A. **The constitution of society: Outline of the theory of structuration**. Oakland: University of California Press, 1984. 402 p.

GOFFMAN, E. **The Presentation of Self in Everyday Life**. New York: Doubleday, 1959. 251 p.

HOMANS, G. C. **Social behavior: Its elementary forms**. San Diego: Harcourt Brace, 1974. 352 p.

LINTON, R. **The study of man: an introduction**. New York: Appleton-Century-Crofts, 1936. 503 p.

LINTON, R. **The cultural background of personality**. New York: Appleton-Century-Crofts, 1945. 157 p.

MASLOW, A. H. A theory of human motivation. **Psychological Review**, v. 50, n. 4, p. 370-396, 1943. <https://doi.org/10.1037/h0054346>

OSHER, D. *et al.* Drivers of human development: How relationships and context shape learning and development 1. In: CANTOR, P.; OSHER, D. (Org.). **The science of learning and development**. New York: Routledge, 2021, cap. 2. p. 55-104.

SMITH, J. A.; MOODY, J. Structural effects of network sampling coverage I: Nodes missing at random. **Social Networks**, v. 35, n. 4, p. 652-668, 2013.
<https://doi.org/10.1016/j.socnet.2013.09.003>

STEELE, C. M. The Psychology of Self-Affirmation: Sustaining the Integrity of the Self. **Advances in Experimental Social Psychology**, v. 21, p. 261-302, 1988.
[https://doi.org/10.1016/S0065-2601\(08\)60229-4](https://doi.org/10.1016/S0065-2601(08)60229-4)

TINTO, V. (1993). **Leaving college**: Rethinking the causes and cures of student attrition. Chicago: University of Chicago Press, 1993. 312 p.

VYGOTSKY, L. S. **Thought and Language**. Cambridge: MIT Press, 1962. 168 p.

VYGOTSKY, L. S. **Mind in society**: The development of higher psychological processes. Cambridge: Harvard University Press, 1978. 159 p.

WASSERMAN, S.; FAUST, K. **Social network analysis**: Methods and applications. Cambridge: Cambridge University Press, 1994. 857 p.

WENGER, E. **Communities of practice**: Learning, meaning, and identity. Cambridge: Cambridge University Press, 1999. 336 p.

WERTSCH, J. V. **Vygotsky and the social formation of mind**. Cambridge: Harvard University Press, 1988. 280 p.

WERTSCH, J. V. **Voices of the mind**: A sociocultural approach to mediated action. Cambridge: Harvard University Press, 1991. 169 p.

Apêndice A - 52 artigos analisados na revisão de literatura

ALCOCK, L. *et al.* Study habits and attainment in undergraduate mathematics: A social network analysis. **Journal for Research in Mathematics Education**, v. 51, n. 1, p. 26-49, 2020. <https://doi.org/10.5951/jresmetheduc.2019.0006>

ASSIS, B. D. S. D. *et al.* Frequent pattern mining augmented by social network parameters for measuring graduation and dropout time factors: A case study on a production engineering course. **Socio-Economic Planning Sciences**, v. 81, p. 101200, 2022.
<https://doi.org/10.1016/j.seps.2021.101200>

BENBOW, R. J.; LEE, Y. G. Exploring student service member/veteran social support and campus belonging in university STEMM fields. **Journal of College Student Development**, v. 63, n. 6, p. 593-610, 2022. <https://doi.org/10.1353/csd.2022.0050>

BERHAN, L. M. *et al.* Social Networks Analysis of African American Engineering Students at a PWI and an HBCU—A Comparative Study. *In: ASEE ANNUAL CONFERENCE & EXPOSITION PROCEEDINGS*, 2019, Tampa. **Atas** [...]. Washington: ASEE, 2019. <https://doi.org/10.18260/1-2--32253>

BODA, Z. *et al.* Short-term and long-term effects of a social network intervention on friendships among university students. **Scientific Reports**, v. 10, n. 1, p. 2889, 2020. <https://doi.org/10.1038/s41598-020-59594-z>

BREWE, E.; KRAMER, L. H.; O'BRIEN, G. E. Changing participation through formation of student learning communities. *In: AIP CONFERENCE PROCEEDINGS*, 2010, Madrid. **Atas** [...]. College Park: AIP, 2010. p. 85-88. <https://doi.org/10.1063/1.3515255>

BREWE, E.; KRAMER, L.; SAWTELLE, V. Investigating student communities with network analysis of interactions in a physics learning center. **Physical Review Special Topics Physics Education Research**, v. 8, n. 1, p. 010101, 2012. <https://doi.org/10.1063/1.3266688>

BROWN, M. The push and pull of social gravity: How peer relationships form around an undergraduate science lecture. **The Review of Higher Education**, v. 43, n. 2, p. 603-632, 2019. <https://doi.org/10.1353/rhe.2019.0112>

BRUUN, J.; BREWE, E. Talking and learning physics: Predicting future grades from network measures and Force Concept Inventory pretest scores. **Physical Review Special Topics - Physics Education Research**, v. 9, n. 2, p. 020109, 2013. <https://doi.org/10.1103/PhysRevSTPER.9.020109>

COMMEFORD, K.; BREWE, E.; TRAXLER, A. Characterizing active learning environments in physics using network analysis and classroom observations. **Physical Review Physics Education Research**, v. 17, n. 2, p. 020136, 2021. <https://doi.org/10.1103/PhysRevPhysEducRes.17.020136>

CRESPO, P. T.; ANTUNES, C. Predicting teamwork results from social network analysis. **Expert Systems**, v. 32, n. 2, p. 312-325, 2015. <https://doi.org/10.1111/exsy.12038>

CROSSETTE, N.; CARR, L. D.; WILCOX, B. R. Correlations between student connectivity and academic performance: A pandemic follow-up. **Physical Review Physics Education Research**, v. 19, n. 1, p. 010106, 2023.

<https://doi.org/10.1103/PhysRevPhysEducRes.19.010106>

DOU, R.; BREWE, E. Network centrality and student self-efficacy in an interactive introductory physics environment. *In: PHYSICS EDUCATION RESEARCH CONFERENCE PROCEEDINGS*, 2014, Minneapolis. **Atas** [...]. College Park: AAPT, 2014. p. 67-70. <https://doi.org/10.1119/perc.2014.pr.013>

DOU, R. *et al.* Beyond performance metrics: Examining a decrease in students' physics self-efficacy through a social networks lens. **Physical Review Physics Education Research**, v. 12, n. 2, p. 020124, 2016. <https://doi.org/10.1103/PhysRevPhysEducRes.12.020124>

DOU, R. *et al.* Understanding the development of interest and self-efficacy in active-learning undergraduate physics courses. **International Journal of Science Education**, v. 40, n. 13, p. 1587-1605, 2018. <https://doi.org/10.1080/09500693.2018.1488088>

DOU, R.; ZWOLAK, J. P. Practitioner's guide to social network analysis: Examining physics anxiety in an active-learning setting. **Physical Review Physics Education Research**, v. 15, n. 2, p. 020105, 2019. <https://doi.org/10.1103/PhysRevPhysEducRes.15.020105>

FIRE, M. *et al.* Predicting student exam's scores by analyzing social network data. *In: PROCEEDINGS OF ACTIVE MEDIA TECHNOLOGY: 8TH INTERNATIONAL CONFERENCE*, 2012, Macau. **Atas** [...]. Berlin: Springer Berlin Heidelberg, 2012. p. 584-595. https://doi.org/10.1007/978-3-642-35236-2_59

FORSMAN, J.; MOLL, R.; LINDER, C. Extending the theoretical framing for physics education research: An illustrative application of complexity science. **Physical Review Special Topics-Physics Education Research**, v. 10, n. 2, p. 020122, 2014.

<https://doi.org/10.1103/PhysRevSTPER.10.020122>

GOERTZEN, R. M.; BREWE, E.; KRAMER, L. Expanded markers of success in introductory university physics. **International Journal of Science Education**, v. 35, n. 2, p. 262-288, 2013. <https://doi.org/10.1080/09500693.2012.718099>

GRUNSPAN, D. Z. *et al.* Males under-estimate academic performance of their female peers in undergraduate biology classrooms. **PloS one**, v. 11, n. 2, p. e0148405, 2016.

<https://doi.org/10.1371/journal.pone.0148405>

HAN, S.; OH, E. G.; KANG, S. P. Social Capital Leveraging Knowledge-Sharing Ties and Learning Performance in Higher Education: Evidence from Social Network Analysis in an Engineering Classroom. **AERA Open**, v. 8, n. 1, p. 1-15, 2022. <https://doi.org/10.1177/23328584221086665>

HASS, C. A. *et al.* Studying community development: a network analytical approach. *In*: 2018 PHYSICS EDUCATION RESEARCH CONFERENCE PROCEEDINGS, 2018, Washington. **Atas** [...]. College Park: AAPT. <https://doi.org/10.1119/perc.2018.pr.Hass>

HUERTA-MANZANILLA, E. L.; OHLAND, M. W.; LONG, R. A. The Impact of Social Integration on Engineering Students' Persistence, Longitudinal, Interinstitutional Database Analysis. *In*: ASEE ANNUAL CONFERENCE & EXPOSITION PROCEEDINGS, 2013, Atlanta. **Atas** [...]. Washington: ASEE, 2013. <https://doi.org/10.18260/1-2--22596>

HUERTA-MANZANILLA, E. L.; OHLAND, M. W.; PENICHE-VERA, R. D. R. Co-enrollment density predicts engineering students' persistence and graduation: College networks and logistic regression analysis. **Studies in Educational Evaluation**, v. 70, p. 101025, 2021. <https://doi.org/10.1016/j.stueduc.2021.101025>

JEFFREY, W. *et al.* STEM learning communities promote friendships but risk academic segmentation. **Scientific Reports**, v. 12, n. 1, p. 12442, 2022. <https://doi.org/10.1038/s41598-022-15575-y>

OLIVARES, D. *et al.* Using social network analysis to measure the effect of learning analytics in computing education. *In*: IEEE INTERNATIONAL CONFERENCE ON ADVANCED LEARNING TECHNOLOGIES (ICALT), 19TH, 2019, Maceió. **Atas** [...]. New York: IEEE, 2019. p. 145-149 <https://doi.org/10.1109/ICALT.2019.00044>

POMIAN, K. E. *et al.* Using social network analysis on classroom video data. *In*: 2017 PHYSICS EDUCATION RESEARCH CONFERENCE PROCEEDINGS, 2017, Cincinnati. **Atas** [...]. College Park: AAPT. <https://doi.org/10.1119/perc.2017.pr.074>

POWAZNY, S.; KAUFFELD, S. The impact of influential others on student teachers' dropout intention—A network analytical study. **European Journal of Teacher Education**, v. 44, n. 4, p. 520-537, 2021. <https://doi.org/10.1080/02619768.2020.1793949>

PULGAR, J.; RIOS, C.; CANDIA, C. Physics problems and instructional strategies for developing social networks in university classrooms. **Arxiv Preprint**, 2019. <https://arxiv.org/pdf/1904.02840>

PULGAR, J.; CANDIA, C.; LEONARDI, P. M. Social networks and academic performance in physics: Undergraduate cooperation enhances ill-structured problem elaboration and inhibits well-structured problem solving. **Physical Review Physics Education Research**, v. 16, n. 1, p. 010137, 2020. <https://doi.org/10.1103/PhysRevPhysEducRes.16.010137>

RAMSEY, L. R. *et al.* Classroom connections: A social network analysis of STEM students at a regional university. **Journal of College Student Retention: Research, Theory & Practice**, v. 0, n. 0, p. 1-23, 2023. <https://doi.org/10.1177/15210251231215787>

REINHOLZ, D. L. Co-Calculus: Integrating the Academic and the Social. **International Journal of Research in Education and Science**, v. 3, n. 2, p. 521-542, 2017. <https://doi.org/10.21890/ijres.327911>

SALZMAN, N. *et al.* Lasting Impacts of a Summer Bridge and Outdoor Experience Program on Student Relationships: A Social Network Analysis. *In: 2020 ASEE ANNUAL CONFERENCE & EXPOSITION PROCEEDINGS*, 2020, Montreal. **Atas** [...]. Washington: ASEE, 2020. <https://doi.org/10.18260/1-2--35236>

SIMPFENDOERFER, L. N., *et al.* What topics of peer interactions correlate with student performance in physics courses? **European Journal of Physics**, v. 45, n. 3, p. 035704, 2024. <https://doi.org/10.1088/1361-6404/ad358b>

SONNENBERG-KLEIN, J.; ABLER, R. T.; COYLE, E. J. Social network analysis: Peer support and peer management in multidisciplinary, vertically integrated teams. *In: ASEE ANNUAL CONFERENCE & EXPOSITION PROCEEDINGS*, 2018, Salt Lake City. **Atas** [...]. Washington: ASEE, 2018. <https://doi.org/10.18260/1-2--30972>

STADTFELD, C. *et al.* Integration in emerging social networks explains academic failure and success. **Proceedings of the National Academy of Sciences**, v. 116, n. 3, p. 792-797, 2019. <https://doi.org/10.1073/pnas.1811388115>

SUNDSTROM, M. *et al.* Examining the effects of lab instruction and gender composition on intergroup interaction networks in introductory physics labs. **Physical Review Physics Education Research**, v. 18, n. 1, p. 010102, 2022. <https://doi.org/10.1103/PhysRevPhysEducRes.18.010102>

SUNDSTROM, M.; KAGEORGE, L. Investigating peer recognition across an introductory physics sequence: Do first impressions last? **Physical Review Physics Education Research**, v. 20, n. 1, p. 010133, 2024. <https://doi.org/10.1103/PhysRevPhysEducRes.20.010133>

TRAXLER, A. L. *et al.* Network positions in active learning environments in physics. **Physical Review Physics Education Research**, v. 16, n. 2, p. 020129, 2020. <https://doi.org/10.1103/PhysRevPhysEducRes.16.020129>

TURETSKY, K. M. *et al.* A psychological intervention strengthens students' peer social networks and promotes persistence in STEM. **Science Advances**, v. 6, n. 45, p. eaba9221, 2020. <https://doi.org/10.1126/sciadv.aba9221>

VARGAS, D. L. *et al.* Correlation between student collaboration network centrality and academic performance. **Physical Review Physics Education Research**, v. 14, n. 2, p. 020112, 2018. <https://doi.org/10.1103/PhysRevPhysEducRes.14.020112>

WALSH, C.; KUSHALIEV, D.; HOLMES, N. G. (2020). Connecting the dots: Student social networks in introductory physics labs. *In: PHYSICS EDUCATION RESEARCH CONFERENCE PROCEEDINGS*, 2020, Online. **Atas** [...]. College Park: AAPT. 557-562. <https://doi.org/10.1119/perc.2020.pr.Walsh>

WELLS, J. E. Modeling student collaborations using valued ERGMs. *In: 2019 PHYSICS EDUCATION RESEARCH CONFERENCE PROCEEDINGS*, 2019, Provo. **Atas** [...]. College Park: AAPT. p. 633-638. <https://doi.org/10.1119/perc.2019.pr.Wells>

WILLIAMS, E., *et al.* Understanding centrality: Investigating student outcomes within a classroom social network. *In: 2015 PHYSICS EDUCATION RESEARCH CONFERENCE PROCEEDINGS*, 2015, Greenbelt. **Atas** [...]. College Park: AAPT. p. 375-378. <https://doi.org/10.1119/perc.2015.pr.089>

WILLIAMS, E. A. *et al.* Engagement, integration, involvement: supporting academic performance and developing a classroom social network. **Arxiv Preprint**, 2017. <https://arxiv.org/pdf/1706.04121.pdf>

WILLIAMS, E. A. *et al.* Linking engagement and performance: The social network analysis perspective. **Physical Review Physics Education Research**, v. 15, n. 2, p. 020150, 2019. <https://doi.org/10.1103/PhysRevPhysEducRes.15.020150>

WOLF, S. F. *et al.* Social network development in classrooms. **Applied Network Science**, v. 7, n. 1, p. 24, 2022. <https://doi.org/10.1007/s41109-022-00465-z>

YANG, Y. *et al.* A study of informal learning communities: A tale of two physics courses. *In*: 2014 PHYSICS EDUCATION RESEARCH CONFERENCE PROCEEDINGS, 2014, Minneapolis. **Atas** [...]. College Park: AAPT. p. 283-286.
<https://doi.org/10.1119/perc.2014.pr.067>

ZANDER, L. *et al.* Academic self-efficacy, growth mindsets, and university students' integration in academic and social support networks. **Learning and Individual Differences**, v. 62, p. 98-107, 2018. <https://doi.org/10.1016/j.lindif.2018.01.012>

ZWOLAK, J. P.; BREWE, E. The impact of social integration on student persistence in introductory Modeling Instruction courses. *In*: PHYSICS EDUCATION RESEARCH CONFERENCE PROCEEDINGS, 2015, Greenbelt. **Atas** [...]. College Park: AAPT. p. 395-398. <https://doi.org/10.1119/perc.2015.pr.094>

ZWOLAK, J. P. *et al.* Students' network integration as a predictor of persistence in introductory physics courses. **Physical Review Physics Education Research**, v. 13, n. 1, p. 010113, 2017. <https://doi.org/10.1103/PhysRevPhysEducRes.13.010113>

ZWOLAK, J. P.; ZWOLAK, M.; BREWE, E. Educational commitment and social networking: The power of informal networks. **Physical Review Physics Education Research**, v. 14, n. 1, p. 010131, 2018. <https://doi.org/10.1103/PhysRevPhysEducRes.14.010131>



Direito autoral e licença de uso: Este artigo está licenciado sob uma [Licença Creative Commons](https://creativecommons.org/licenses/by-nc-nd/4.0/).