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Networks in Learning Analytics: Where Theory, Methodology, and Practice Intersect

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Abstract

Network analysis has contributed to the emergence of learning analytics. In this editorial, we briefly introduce network science as a field and situate it within learning analytics. Drawing on the Learning Analytics Cycle, we highlight that effective application of network science methods in learning analytics involves critical considerations of learning processes, data, methods and metrics, and interventions, as well as ethics and value systems surrounding these areas. Careful work must meaningfully situate network methods and interventions within the theoretical assumptions explaining learning, as well as within pedagogical and technological factors shaping learning processes. The five empirical papers in the special section demonstrate diverse applications of network analysis, and the invited commentaries from cognitive network science and physics education research further discuss potential synergies between learning analytics and other sister fields with a shared interest in leveraging network science. We conclude by discussing opportunities to strengthen the rigour of network-based learning analytics projects, expand current work into nascent areas, and achieve more impact by holistically addressing the full cycle of learning analytics.

Keywords

Network science, network analysis, networked learning, social network analysis, learning analytics

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1. Introduction

Network analysis — especially social network analysis — has been identified as a key contributor to the emergence of learning analytics (Siemens, 2013). Long before the first International Conference on Learning Analytics and Knowledge (LAK '11) in 2011, network analysis was used to understand social processes related to learning and communication in groups (Scott, 2013). In learning analytics, early applications of network analysis focused on deriving analytical insights into learning (Haythornthwaite, 2011), as well as providing real-time practical feedback on student communication (Bakharia & Dawson, 2011).

The uptake of network analysis in learning analytics is not surprising given the versatility of network analysis in providing analytical, computational, and representational support for the analysis of teaching and learning. Analytically, network analysis offers a suite of methods to derive network metrics useful for characterizing learning and learners (Gašević et al., 2013; Göhnert et al., 2013; Lund & Suthers, 2016). Computationally, contemporary software packages of network analysis offer tools that handle larger volumes of data generated in digital learning environments (Haythornthwaite & De Laat, 2012; Siemens, 2005). Representationally, network visualizations provide unique affordances for communicating patterns about relationships and interactions such as who talked to whom (Bakharia & Dawson, 2011). The myriad ways network analysis can be leveraged to examine learning have made it a popular topic in learning analytics.

1.1. Background to the Special Section

Despite its utility and versatility, network analysis also faces methodological challenges when it is applied in learning analytics. During recent LAK conferences, a workshop series has been organized to deliberate these issues (Poquet et al., 2020, 2021a, 2021b) building on growing awareness of analytic choices in network construction and validity issues of network metrics (e.g., Wise et al., 2017). The workshops led to recommendations outlining methodological considerations important for network studies in learning analytics. Some of these considerations are technical, focused on consistent reporting practices (Poquet et al., 2021b). Others illuminate the interdisciplinary nature of network analysis in learning settings, surfacing contradictions between social science theory undergirding network metrics and the learning context where network analysis is applied. Based on this recognition, authors are recommended to explicitly justify the choice and interpretation of metrics, as well as theory-driven decisions made in network construction (Poquet et al., 2021b).

Following the LAK workshop series, with support from workshop co-chair Dr. Tobias Hecking, we called for submissions to this special section in the *Journal of Learning Analytics* that would push the frontiers of the current work through empirical studies, conceptual papers, new analytical approaches, or designs of learning technologies that use networks. The five accepted papers demonstrate a great variety of applications of network analysis using different data sources across diverse contexts. In this issue, Saqr and López-Pernas revisit an ongoing discussion on the relevance of centrality measures; Stasewitsch et al. investigate the role of innovator networks in educational settings; Zhang et al. tackle the question of learner attention online using network perspective; Malmberg et al. examine the relationships between self-regulation phases borrowing approaches from the networks of variables; and Mallavarapu et al. examine social potentialities in the informal settings of museum learning. In addition to the diverse set of empirical studies, to inspire other uses of networks in learning, the special section includes two invited commentaries: one on research about interaction networks in physics education research by Traxler, and another on networks in cognitive science by Siew. Collectively, this special section presents state-of-the-art research spanning networks in learning.

1.2. Key Concepts and Questions in Applying Network Analysis to Learning Settings

Besides introducing these papers and commentaries, this editorial also aspires to provide a useful guide for research on networks in learning settings. To make the editorial accessible to a wide audience, we briefly introduce main concepts and goals of network science, a rapidly developing research field where methodological innovations in network analysis are taking place. We then discuss the relationship between network science and network research in learning analytics, outlining different ways in which learning analytics can intersect with network science, beyond the methodological aspect itself. Drawing on the Learning Analytics Cycle, which includes learning processes, data, metrics, and interventions (Clow, 2012), we raise questions salient in our discussions during the past workshops:

- Is network construction theoretically informed and contextually reasonable (*Does theory align with the context*)?
- Are network analytical decisions sufficiently explained for transparency and replicability as well as practical actions (*Are data, context, and metrics sufficiently described*)?
- Are network analysis methods congruent with the studied phenomenon (*Do metrics align with the context*)?
- Are pedagogical actions suggested by network analytics sensitive to important values held by stakeholders (*Are interventions valuable to all stakeholders*)?
- How can learning analytics be inspired by network science and other communities working on the intersection of networks and learning (*What other theories can inform this context*)?

By anchoring these questions in the Learning Analytics Cycle, we provide a framework for situating a particular network study in the cycle, while showcasing the importance of attending to all areas of the cycle in a study. By doing so, we argue that strong research contributions in the area of networks and learning analytics require enrichment of theory, but also alignment of theory, data, and method, as well as linkages to tools and feedback practices. We argue that while network science can be connected to learning analytics through one of these areas — theoretical, pedagogical, technological, methodological, practical — more powerful cases require integrated consideration of these areas.

2. Network Science in Learning Analytics

2.1. What is Network Science?

Network science as a field of study emerged in the 21st century, even though its roots in mathematical graph theory and sociology are decades old. The fast rise of this research area was fuelled by the availability of diverse network maps across social domains that enabled researchers to identify universal properties across them (Barabási, 2016). Network science has benefited from the increased availability of digital data (e.g., from social media platforms) and advanced computational capabilities. It is broadly applied in various disciplines and domains including physics, biology, neuroscience, geography, and public policy, just to name a few (National Research Council, 2005). Recent developments in network science have given rise to new research domains including networked communication (Welles & González-Bailón, 2020), networks in cognitive science (Baronchelli et al., 2013), and network psychometrics (Epskamp et al., 2017).

Networks can be useful in many ways, including abstracting a phenomenon so that it maintains its relational and structural properties, representing processes within network structures, and guiding actions in practice. First, networks provide an integrative mechanism of abstraction that maintains interconnectedness essential for a wide range of phenomena (Newman, 2018). Such abstraction emphasizes the importance of connections, allowing researchers to ask questions about relations, positions, and structures. For example, the World Wide Web is resistant to failures due to its network property of having a small number of dominant nodes that connect many other nodes (Barabási & Bonabeau, 2003). The network perspective is conducive to discovering such insights. Second, network analysis affords ways to examine processes that operate through the network structure. For example, commercial goods travel through the transportation networks; infectious diseases spread on networks; information diffuses on online social networks. Network science affords approaches to investigating these dynamic network processes. Finally, network analysis and thinking enable us to take concrete actions based on networks, ranging from adjusting organizational practice, to mitigating transmissive diseases, to countering misinformation (Barabási, 2016; Budak et al., 2011).

While network science may sound attractive, or even fashionable, there are common pitfalls to be avoided when applying network thinking and network analysis. A network includes two basic elements: *nodes* that represent entities (such as people, artifacts, words, neurons) and *edges* that indicate the relations among them (such as collaboration, shared usage, semantic similarity, synapse connection). Identifying and operationalizing these two basic elements — nodes and edges — are essential for a network study. Important questions about network construction include these: What do the nodes and links represent? Is the constructed network model aligned with the phenomenon? How do we make sense of a network metric (such as betweenness centrality) in the studied context? Are the actions suggested by network analysis practically sound? These questions need to be carefully interrogated and are acutely important when digital system logs are used to construct networks (Howison et al., 2011) due to the inferences necessarily made from log-files (Oshima & Hoppe, 2021). Without considering these questions, network analysis becomes conceptually vacuous, devoid of solid grounding in context, and becomes a pursuit of "a holy grail" without much rigour (Knox et al., 2006, p. 129). Indeed, a network analysis can be only as good as the network model it is based on (Butts, 2009). This point is illuminated in domains such as biology, neuroscience, geography, and cosmology (Bassett & Sporns, 2017; Krioukov et al., 2012; Uitermark & van Meeteren, 2021), and needs to be recognized wherever network science is applied.

With a solid grounding, advances in network science can be leveraged to examine complex phenomena in various domains. Network science is pushing the frontiers in several directions. For instance, beyond simple unimode, uniplex networks, a network could also include different types of nodes (i.e., multi-mode) and edges (i.e., multiplex), leading to more sophisticated networks, such as bipartite networks that involve two types of nodes and links between nodes of different types (Hoppe, 2017). Similarly, nodes can be placed on different layers, forming multilayer networks useful for examining real-world systems such as socio-ecological systems (Boccaletti et al., 2014; Bodin & Tengö, 2012) and collaborative discourse (Chen et al., 2022). Recent innovations in hypergraph analysis enable formal analysis of many constellations of diverse nodes and various sets of edges (de Arruda et al., 2020). The temporal dimension of networks has also received considerable attention, leading to nascent toolkits such as stochastic actor-based models (Snijders et al., 2010) and relational event modelling (Butts, 2008) invented to examine dynamics in networks. Combining network analysis with the deep learning paradigm, researchers have also developed algorithms to project network entities to vector spaces in a way that captures the network structure (Béres et al., 2019; Perozzi et al., 2014). The vector representation, or graph embeddings in other words, can be leveraged by other computational tasks such as similarity search and link prediction to generate actionable insights (Zhang et al., 2021). In summary, network science as a field is advancing quickly thanks to contributions from different disciplines. In turn, network science also informs problem definition, research methods, and practical interventions in various domains.

2.2. Situating Network Science in Learning Analytics

Many types of empirical data about learning — e.g., friendship ties in the classroom, social interactions in forums, word connections in think-alouds, co-enrollment in courses — can be examined using network approaches. However, the ways in which network science methods are applied in learning analytics vary greatly to an extent where coherent insights become difficult to draw. To highlight this problem, Poquet and Joksimovic (2022) characterize network studies in learning analytics as "cacophony." They argue that while the versatility of network science methods allow them to be applied to various research problems related to learning, this same versatility also creates possibilities for naive applications of network analysis.

Sophisticated application of network science in learning analytics requires integrated considerations of theoretical, methodological, and contextual factors of learning. For a learning analytics project, its design needs to step "from clicks to constructs" in a principled way (Knight & Buckingham Shum, 2017), simultaneously attending to multiple facets of rigour (Reeves, 2011), respecting contextual factors (Wise et al., 2021), addressing insights that contribute to the feedback loop (Clow, 2012), and also surfacing socio-political narratives undergirding education more broadly (Philip & Sengupta, 2021). Addressing these multifaceted requirements in learning analytics research is not easy.

To help researchers grapple with the various aspects essential for learning analytics, we highlight the pillars of quality network studies in learning analytics. These pillars to a learning analytics project are akin to legs to the table — they need to be in balance; otherwise the table is lopsided. Drawing on the Learning Analytics Cycle defined by Clow (2012), effective application of network science methods in learning analytics involves four interconnected steps: 1) learning processes, 2) data,

3) methods and metrics, and 4) interventions (see Figure 1). We further recognize that these steps need to be underpinned by value-sensitive and ethical choices. Below we explicate how these areas are reflected in extant network studies in learning analytics.

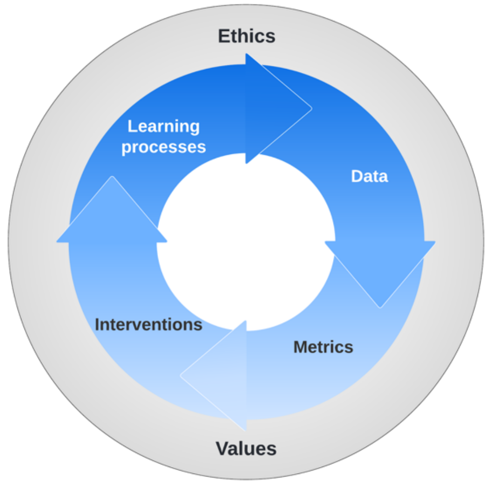

Figure 1. The adapted Learning Analytics Cycle.

Network studies in learning analytics have so far concentrated on innovations in the methods part of this cycle, with a large body of research experimenting with various network techniques in small-scale correlational studies (Dawson et al., 2019). Such a focus on methods and metrics of network analysis is not surprising. When discussing the connection between network science and learning analytics, the initial impression for many people is that network science provides a suite of methods — analytical procedures, metrics, visualizations — for investigating learning in various settings. These network science methods enable researchers to detect and characterize patterns in learning data. Network metrics, such as betweenness centrality in student networks, can capture learning constructs that are difficult to measure using other methods, and can be then linked with other variables such as learning performance (e.g., Dado & Bodemer, 2017; Gardner & Brooks, 2018). However, adopting network analysis simply because of its methodological appeals endangers the rigour of learning analytics research and practice.

Another area in the cycle receiving some attention, especially in early studies, is the practical value of using network science to support pedagogical interventions in education. As with the premise of other learning analytics applications such as student dropout prediction, network science can provide actionable insights when learning is still taking place. SNAPP (Social Networks Adapting Pedagogical Practice), for instance, was designed to guide pedagogical practice based on real-time network analysis of learner interaction in discussion forums (Bakharia & Dawson, 2011). This work has spurred the emergence of Social Learning Analytics interested in enabling pedagogical actions based on visual and quantitative analyses of patterns in social learning (Buckingham Shum & Ferguson, 2012; Chen et al., 2018). Besides human networks, networks of words are also constructed based on their co-occurrence in online posts to prompt student reflection on collaborative knowledge building (Feng et al., 2021). While these interventions contribute novel toolkits for improving learning, emergent work in learning analytics has begun to shed light on the nuanced process of instructor sensemaking and pedagogical action-taking (Li et al., 2021; van Leeuwen et al., 2017), which are also important for network-based learning analytics projects.

The other two areas of the cycle — learning processes and data — often get sidelined in network studies of learning analytics. Explicating these two areas requires us to surface theoretical, pedagogical, and technological factors in learning. While network analysis can be applied to any type of learning, such as individual learning from MOOC videos (Zhang et al., 2022, this issue), many learning theories and pedagogies are strongly informed by network perspectives. Learning is a fundamentally social process, involving rich human dialogues (Wegerif, 2012; Vygotsky, 1978), mediated interactions, and creation of artifacts in social networks (Siemens, 2005; Stahl & Hakkarainen, 2021). Theoretical perspectives as such have a widespread footprint in education, shaping pedagogical practices and technological designs meant to support particular conceptions of learning. As a result, data generated in particular learning processes need to be recontextualized in these theoretical, pedagogical, and technological decisions when making proper interpretation. For example, Knowledge Building is a theory and pedagogy that involves learners working collectively on improving ideas (Scardamalia & Bereiter, 2014). While its technological environment, Knowledge Forum, may look similar to a discussion forum, the analysis of its data needs to be grounded in the pedagogy's discussion practices that prioritize idea improvement over socialization or argumentation. In this case, student communication networks in Knowledge Forum, as well as any metrics generated by network analysis, need to be interpreted in relation to the mission of collective idea improvement. When these theoretical ideas about the purpose of the network are added to network metrics, the metrics need to be interpreted in new ways, different from the interpretations generated in other contexts where these theoretical ideas do not apply. Moving forward, effective application of network analysis needs to foreground learning processes and data in the cycle to make rigorous contributions to research and practise.

Moreover, the cycle needs to engage values and ethics explicitly in every step: from theories of learning (Philip & Sengupta, 2021), to design choices made in a visualization (Chen & Zhu, 2019), to the framing of pedagogical interventions (Wise, 2014). We need to inspect value assumptions in network analysis of learning that may, for instance, position less connected students as being "socially isolated" or "at risk." Such assumptions stem from theories of learning and society, cultural norms, or hidden curricula representing values and beliefs held by certain social groups. Ethics in the cycle goes beyond traditional ethical considerations with research to treat learning analytics as an ethical and moral practice that proactively considers the consequences of algorithms and systems (Prinsloo & Slade, 2017). Network analysis introduces novel issues in these areas (Chen & Zhu, 2019), which need to be properly addressed in all steps of the learning analytics cycle.

While a learning analytics project using network science may mainly contribute to one or a few parts of the cycle, ideally the project would attend to the full cycle, ensuring that different parts of the cycle are congruent. When integrating network science in learning analytics, careful work needs to meaningfully situate methods and interventions in these theoretical, pedagogical, and technological factors.

3. Overview of the Special Section Papers

Building on previous workshops at the LAK conference, this special section of the *Journal of Learning Analytics* deepens the conversation by including five empirical papers representing different learning theories, contexts, data types, network methods, and opportunities for action taking. We briefly summarize these papers from the perspective of how they reflect different parts of the adapted Learning Analytics Cycle described in the previous section (see Table 1). In addition to these papers, this special section also includes two invited commentaries that present critical analyses of the papers and discuss the intersection of network science and learning analytics.

In "The Curious Case of Centrality Measures: A Large-Scale Empirical Investigation," Saqr and López-Pernas (2022, this issue) return to the analysis frequently favoured in learning analytics work on student communication networks. Namely, the authors apply meta-analysis to 69 cases that examine the relationship between network centrality of a student in a course online forum and the student grade. This study provides larger support to what has been shown in smaller-scale analysis — that the number of direct connections is most likely associated with performance. Despite its limited attention to theoretical, pedagogical, and technological aspects, the study presents an interesting effort to extend prior work, seeking convergence across empirical studies. The findings show that network metrics directly related to student activity correlate with performance. More nuanced network metrics relate to performance in diverse results. The study shows that generalizations across courses remain limited unless pedagogical and technological course aspects are also generalized sufficiently, which motivates a shift in a new generation of network centrality measures.

In "Video Features, Engagement, and Patterns of Collective Attention Allocation: An Open Flow Network Perspective," Zhang, Huang, and Gao (2022, this issue) propose an ecological system perspective of video-watching behaviours in massive open online courses (MOOCs) by focusing on the flow of *collective attention* within an open system. Using MOOC clickstream data, they construct an open-flow network that includes video resources as nodes and the flows of navigation behaviours between resources as links. By constructing this network, a suite of network metrics are computed for each video resource to measure its accumulation, dissipation, and circulation of collective attention. These metrics could be used to evaluate the effectiveness of instructional videos for attracting user attention and facilitating effective learning sequences.

In "Exploring the Utility of Social-Network-Derived Collaborative Opportunity Temperature Readings for Informing Design and Research of Large-Group Immersive Learning Environments," Mallavarapu, Lyons, and Uzzo (2022, this issue) recognize the significance of the physical dimension of learning spaces and examine potential co-located collaboration in a museum setting. Applying multimodal analytics and social network analysis to video data, they detect visitors using OpenPose, construct Collaborative Opportunity Networks by linking visitors within a 2.1 metre social proxemic distance, analyze subgroup structures in the networks, and derive an indicator, Collaborative Opportunity Temperature, to capture the distribution of different structural signatures (i.e., singletons, coteries, crowds, and clubs) in the group of visitors in front of an exhibit. This measure can be mapped temporally to provide valuable insights to both exhibit curators and researchers while also protecting the privacy of museum visitors.

In "How the Monitoring Events of Individual Students Are Associated with Phases of Regulation – A Network Analysis Approach," Malmberg, Saqr, Järvenoja, and Järvelä (2022, this issue) investigate student monitoring and regulation in collaborative learning processes. Drawing on qualitative coding of video data, they construct a time series of monitoring codes and use graphical vector autoregression (VAR; Epskamp et al., 2017) to reveal the temporal contingencies among different categories of monitoring. VAR estimates a network that contains codes as nodes and links among nodes as temporal correlations, allowing them to analyze the temporal dynamics of monitoring events in collaborative learning. The study utilizes the idiographic approach, where intensive individual-level data are heavily drawn upon to understand individual variability. The network approach taken up by the authors departs from many conventional approaches to network analysis in social science literature, following network psychometrics. The study demonstrates how an idiographic approach in learning analytics can support the examination of a theory, self-regulation theory in this case, when only small datasets are available to instructors in teaching-learning scenarios.

In "Knowledge Transfer in a Two-Mode Network between Higher Education Teachers and their Innovative Teaching Projects," Stasewitsch, Barthauer, and Kauffeld (2022, this issue) take advantage of archival data from a university-wide innovation in teaching and learning funding scheme. The authors construct educational innovation networks of university instructors and projects to examine knowledge transfer and diffusion of innovation. The instructor–project networks spanned five years, with over 200 faculty working in small groups. The authors present insights from theory-informed hypotheses that highlight the structure and effectiveness of this innovation network in educational institutions. The study uses several theories to frame its analysis of workplace learning in organizations such as a university. This study also preserves the structure of the data by constructing instructor–project networks rather than projecting them into human networks of instructors. Methodologically, the authors combine a case-study approach with statistical investigations, extrapolating recommendations for practice.

Table 1. Overview of Papers in the Special Section

Papers	Learning processes: Theoretical, pedagogical, technological context	Data and Metrics: Methodological operationalization	Interventions: Potentiality for practical insight
Saqr & López-Pernas	Communication in online forums in courses based on problem-based learning	Student-to-student networks projected from individual students replying in online forums, with "non-collaborative" posts removed from the analysis	Generalize the relationship between online posting activity and performance, can be added to course-design agnostic predictive models
Zhang et al.	Ecological view of video-based learning in MOOCs reflecting the flow of learners' collective attention to learning resources	Networks of learning resources with links representing the flow of learners' collective attention	Improve the design of MOOC videos based on collective learning behaviours
Mallavarapu et al.	Contextual model of learning in immersive museum exhibits involving sociocultural and physical dimensions	Proximity-based human networks representing possible collaborative engagement	Formative feedback on social engagement in large-group physical spaces
Malmberg et al.	Monitoring and self-regulated learning in collaborative learning processes	Networks of monitoring events constructed based a time series, with the edges representing temporal correlation among events	Guidance for learners to adapt the regulation of learning
Stasewitsch et al.	Knowledge transfer and innovation diffusion in a university-wide project funding educational innovation	Two-mode educational innovation networks of university instructors and the innovation projects they were involved in	Design of network structures among professional staff to support institutional innovation

Collectively, these studies cover learning in a wide range of settings, including individual learning in MOOCs, collaborative problem solving, informal learning in museums, and innovation in organizations. They also demonstrate different methods of network construction and the distinct ways network science methods can be used to examine learning constructs such as students' self-regulation in collaborative tasks, collective attention to instructional videos, and potential co-located collaboration in physical spaces (see Table 1). To complement these empirical studies representing diverse uses of networks in learning analytics, this special section also includes contributions from two experts working with networks and learning in other domains. An invited commentary by Traxler (2022, this issue) brings in views on networks and learning from a physics education research perspective, presenting evidence around interpersonal engagement networks in STEM classes. The second commentary by Siew (2022, this issue) reviews work from cognitive science, explaining how networked knowledge representations are modelled by cognitive scientists. Both fields offer rich examples of applications and evidence to advance this area of work in learning analytics.

Applied research domains that study how to support the teaching of STEM subjects, for instance, such as physics education research (PER), have much to offer to learning analytics. Traxler's commentary (2022, this issue) provides a snapshot of research around student networks derived from student-reported data about their interpersonal engagement in physics classes. As Traxler demonstrates, PER has consistently examined pedagogical designs in physics classes in relation to the structures of varying self-reported student networks. This work offers indicators of interpersonal engagement and relates them to the pedagogical designs in STEM subjects (here, in physics). Traxler explains contemporary issues of social network analysis, such as the non-trivial matter of collecting student demographic data that presents an authentic representation of student identities (e.g., gender) rather than the simplistic categories existing within student management systems. Traxler also highlights that learning analytics and PER have had complementary foci in the analysis of networks in the classrooms: with learning analytics providing linkages between digital interaction networks, design, and outcomes, whereas PER provides these linkages between perceived student networks. Empirical studies that link digital and perceived student networks, however, have been scarce.

Cognitive network science (CNS) takes a thorough theoretical approach to modelling knowledge representations. In CNS, knowledge representations are modelled through semantic and phonological networks. Siew's commentary (2022, this issue) focuses on the recent work that examined processes related to information retrieval and search in knowledge networks, with the purpose of explaining mechanisms in the study of cognition, such as language processing, memory, and learning, among others. Siew also presents work that shows how network indicators of student concept maps predict student comprehension. She focuses on the statistical models that can be brought into network analysis to simulate processes of interest, enabling inferential analysis of observed data. Although many of the examples presented by Siew remain at the level of individual knowledge representations, in our view, these can be transferred to the analysis of community-level knowledge, as in knowledge building communities.

4. Opportunities and Challenges

Situating network-analytical research within learning analytics offers opportunities and challenges to strengthen future work. The co-evolution of theoretical models, tools used to support learning, and the data generated in learning environments can support rigour and the relevance of insights for teaching and learning.

4.1 Aligning Data with Theories

Examining multiple types of nodes and edges (e.g., Contractor, 2009) with semantic, temporal, or epistemic perspectives integrated (Hecking et al., 2016) presents an opportunity to help align existing theories of learning with potential data sources. Much of network analysis in learning analytics so far has relied on the conceptual principles of social networks constructed from self-reported human relationships; studies are also often limited to descriptive network statistics in one-mode networks of learners (Dado & Bodemer, 2017). Yet, there is little disagreement about the role of artifacts and activities driving learning processes. In socio-technical systems — at the individual, group, and community levels — technology, artifacts, and text mediate processes of learning at different levels and at varying timescales. Networks constructed based on richer types of data sources, beyond more conventional posting behaviours, can help to better represent digital learning in ways that reflect the role of artifacts, activities, and discourse as explanatory factors driving digital learning. Opportunities to advance the alignment between theories and data include exploring multiplex network ties and diverse learning outcomes, examining the relationship between discourse quality and positioning in multiplex networks, and investigating multilayer networks that bring together multiplex ties as separate layers, to describe interrelationships between the students (Traxler, 2022, this issue).

4.2 Aligning Models with Theories

Another opportunity for network research in learning analytics is situated within a stronger focus on explanatory analyses. Mechanisms of social interaction in socio-technical systems may differ from those driving friendship and trust relationships (Chen & Poquet, 2020). Evaluating interventions that affect learning requires an understanding of why and how observed networks change without intervention. Network science has developed simpler models — probabilistic models for random networks or mechanistic models such as preferential attachment (Barabási & Albert, 1999) — that can already be used in digital learning network modelling. Generative models that build on network reconstruction (Hobson et al., 2021) and agent-based models (Wilensky & Rand, 2015) can also be used to understand and enrich theories. Siew (2022, this issue) offers concrete examples of research questions that can align modelling efforts with theories about cognitive networks, such as these: How positioning of concepts within the knowledge structure can help student comprehension, retrieval, and transfer; What mechanisms of cognitive networks develop knowledge representations. Working with modelling processes (such as knowledge flow) through existing network structures in learning settings also presents a potential area of inquiry.

4.3 Aligning Metrics with Situated Interventions

Network metrics have been central to prior work in learning analytics, with prior concerns raised around their validity. Among important next steps is to develop network metrics that can be worked into existing practices. The growing body of research points towards the needed contextualization of the network metrics, i.e., understanding whether metrics in specific pedagogical contexts could be generalized beyond them. Traxler (2022, this issue) suggests that future work can, for instance, focus on overcoming idiosyncrasy between selection of centrality measures, by linking specific pedagogy to the association between centrality measures and performance in student networks of different types (perceived, digital, multiplex). In the same vein, studies linking digital networks with perceived interactions networks can also be contextualized to specific pedagogies (Traxler, 2022, this issue). But perhaps, even more fundamental, is for future work to examine how instructors and learners make sense of network measures and representations in relation to their own practices. The situated nature of interventions requires that researchers understand the sense-making processes specific to understanding relationships, relational data, and their links to learning processes and pedagogies. Questions that need further exploration include those around how network information can be best visualized, whether different learners make sense of network information differently, and how network interventions can be accompanied by pedagogical support that helps learners adjust their practices.

4.4 Aligning Theory, Data, Models, and Interventions with Values

Lastly, the role of values had not been central to network research in learning analytics. This challenging area of inquiry includes inquiries around what kinds of metrics are most valuable to all stakeholders, and how collected data can represent learners more authentically and inclusively (Traxler, 2022, this issue). An important area related to this work is privacy, given the challenge of anonymization within a network structure.

5. Conclusions

Network analysis has contributed to the emergence of learning analytics and still figures as a key area of the field. While the network perspective and methods are appealing for various reasons, future development at the intersection of network science and learning analytics depends on careful consideration of an alignment among theoretical, contextual, methodological, and practical factors. We hope this special section leaves you with an expanded view of applying network science in learning analytics — thanks to contributions from the papers and invited commentaries — as well as specific guidance for launching your own learning analytics project that leverages network science. To move this area forward, we need to look across development in sub-areas of learning analytics, such as collaboration analytics and human-centred learning analytics, for cross-cutting issues concerning rigour and relevance. We can also benefit from cross-fertilizing ideas with other disciplines (such as sociology, business, medicine, physics) that aspire to leverage network science to solve research and practical problems. Ultimately, this work is about seeking ways to better understand learning and making an impact by closing the feedback loop.

Citation Diversity Statement

Recent work in several fields of science has identified a bias in citation practices, where papers from women and minorities are under-cited relative to the number of such papers in the field (Zurn et al., 2020). We have manually checked the first and the last author's names and inferred gender. By this measure, our references are written by woman (first author)/woman (last author) — 8.4% and by solo woman authors — 5.6%; by men (first)/woman (last) — 14.1%; by woman (first)/man (last) — 21.1%; by man (first)/man (last) — 32.4%, and solo man — 18.3%. This method is not indicative of gender identity, and cannot account for intersex, non-binary, or transgender people. We did not infer racial identity either for this case. We look forward to future work that could help us to better understand how to support equitable practices in science.

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