Recommendations for Network Research in Learning Analytics: To Open a Conversation

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Abstract

Network science methods are widely adopted in learning analytics, an applied research area that focuses on the analysis of learning data to understand and improve learning. The workshop, taking place at the 11th International Learning Analytics and Knowledge conference, focused on the applications of network science in learning analytics. The workshop attracted over twenty researchers and practitioners working with network analysis and educational data. The workshop included work-in-progress and group-wide conversations about enhancing the quality of network research in learning analytics. The conversations were driven by concerns around reproducibility and interpretability currently discussed across research communities. This paper presents a snapshot of the workshop discussions beyond its work-in-progress papers. To this end, we summarize a literature review presented to the workshop participants, with the focus on the elements related to the reproducibility and interpretability of network research in education settings. We also provide a summary of the workshop discussions and conclude with suggested guidelines for the reporting of network methods to improve generalizability and reproducibility.

Keywords

Network science, education, learning analytics, learning sciences, recommendations

1. Introduction

Learning analytics (LA) aims to use "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [1, p.1382]. Network analysis (NA) is one of the methodological approaches used in LA. NA enables the modeling and analysis of relational data in education. In essence, a network is composed of a group of entities or elements referred to as nodes or vertices and a relationship that connects them referred to as edges or links. Network visualizations created by NA can be useful in mapping relations and interactions, identifying patterns of interactions, finding active and inactive students, and detecting student or teacher roles. Mathematical analysis of network graphs commonly entails the calculation of indices at the levels of the whole network to show global structural properties or individual nodes/actors comprising the network. Individual-level measures, referred to as centrality measures, can quantify the importance of learners in the network or characterize their roles. Given that the meaning of an actor's importance, roles and contributions is context-specific, centrality measures may vary in their applications and interpretations.

In education, researchers have used NA to meet various analytical goals: to represent interactions among collaborators, to examine mediated communication in Computer-Supported Collaborative Learning (CSCL), to represent and study the relationships among epistemics, to mention a few. To construct a network, many choices must be made by the researcher, for instance, what are the elements

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that need to be studied (nodes), what kind of relationships between them are of interest (edges), and whether the strength of relationship should be considered (weight). These choices influence the constructed network in significant ways, and thereby impact insights based on the researcher's interpretation of the network. While NA could be flexibly applied to various contexts, this advantage raises challenges with selecting network analysis methods and generalizing across contexts.

2. Review of Literature

Researchers aspire to conduct research that can have a societal impact, which needs to be grounded in trustworthy findings that are transferable to various contexts and populations. For research findings to be transferred into practice and policy making, those research findings have to be valid. Two types of validity are essential here: internal validity, a term that refers to the rigorousness of research methods (sampling, data collections, statistical analysis); and external validity, also known as generalizability, a term that refers to whether the results from one sample can be extended to the population or to be applied widely or "externally" in other settings. On the one hand, valid and transferable findings embolden the trust in our methods, help establish impactful practices, and advance the field in general. On the other hand, research without sound methodological rigor endangers our trust. As Bergner put it: "without foregrounding methodological choices in learning analytics we run the risk of generating more doubt" [2, p. 3].

Previous research using NA in learning analytics repeatedly confirmed that variability in research findings can result from methodological choices. Fincham et al. [3] and Wise et al. [4] examined different tie extraction methods in CSCL (direct reply ties, star reply ties, total co-presence, limited co-presence, moving window) on the resulting network and research findings. They found differences in the same analysis applied to the networks constructed with different tie extraction methods. While a significant positive association between centrality measures and academic performance was found in some networks, significant negative association was found in other networks. This work serves as a reminder that tie extraction should be cautiously chosen and justified. Saqr et al. [5] further examined different network configurations and tie weight assignment in multiple courses. Their results similarly show significant differences between network configuration methods as they influence observed correlations between centralities and learning outcomes, such as performance.

Sound methodological choices, valid results, and transparent scientific reporting of the findings are essential for the transferability and reproducibility of the research applying NA in learning analytics. The multifaceted rigor of network research would determine the potential for research findings to influence educational practice and policy making. When applying NA in learning settings, it is important to defining the network model, including its nodes and relations, with the guidance from theory and context. Asking what defines a non-relation in a network and whether the relationships that are excluded comply with that definition, for instance, can help evaluate if the tie definitions were carefully considered. Similar deliberation around the weight and direction of ties is needed. Calculating the network indices either at node or network level relies heavily on these configurations, which is why these choices need to be explained and justified. These choices are essential for the internal validity of network research, as well as the reproducibility and transferability of the research results.

3. Scanning Highly Cited Literature: Methods

To offer a common ground for applying network analysis to the analysis of learning data, we selected fifty most cited papers characterized by the combination of keywords 'network analysis' and 'education' or 'learning'. These most cited studies provide valuable insights into the studies that are highly visible in the field. Because they are highly cited, they set the standard for research practices and offer points of entry for researchers who aspire to conduct network analysis in the field. In February 2021, the authors queried the Web of Science and Scopus databases, with the query: (TITLE-ABS-KEY ("network analysis" AND (education OR learning))) AND PUBYEAR > 2010 AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (LANGUAGE , "English")). All the results returned by the query were sorted by the citation count, and fifty papers with the highest number of citations were selected. Two researchers scanned abstracts of the selected fifty studies to exclude eleven papers that were not relevant, e.g., not analyzing networks related to learning and education. The remaining 39 papers were split between two authors who independently recorded information pertinent to the design, method, and sample of each study. The third author coded a small subset of the studies to calibrate the overall categories used to record information about the papers. During the process, 4 more papers were excluded due to the lack of relevant focus (e.g., focus on infrastructure for learner networks rather than analyzing them), leaving 35 papers to be included in the final analysis.

From each paper we extracted information guided by the coding scheme reported in Table 1. During the workshop, we presented the summary of the dataset to the workshop participants to stimulate group discussions around rigor of network analysis in learning analytics. Here, we report the descriptive summary of the selected papers as well as a summary of group discussions from the workshop. We conclude with suggestions for practical recommendations of reporting data, methods, and analysis conducted in this area of work.

Table 1

Coding categories used to analyze highly cited papers

Category	Explanation
Meta-data	● Authors, journal, pages, title, year published, volume, issue, number of citations
Network modality	● One mode or Two mode
Use of theory	● Was the study theoretically framed? Yes/No ● If yes, what was the theory used to frame the study?
Region	● Where were the participants from (International for MOOCs, otherwise as specified)
Learning Modality	● What was the modality of the educational setting (online, blended, face-to-face)
Sector	● What was the level of the educational setting (higher education, adults/MOOCs, secondary education)
Network size	● What was the size of the network analyzed in the study?
Scope	● How many courses did the study analyze (one, two, three, program-level analysis)
Type of research	● Was the study reporting the results of descriptive or statistical network analysis?
Research question	● What research question was investigated in the study?
Node definition	How were nodes defined in the study?
Edge definition	● How were edges defined in the study? Were they directed or undirected?
Mixed methods	● Was network analysis used in combination with another method?
Descriptive analysis	● Were centralities identified in the study? Were they normalized? Did the study report equations? If sub-graph analysis was a part of the study, what community detection algorithm was used?
Analysis software	● What software was used in the study?
Results	● Does the study offer interpretation of network centrality measures?

4. Results

Table 2 presents the set of thirty-five highly cited papers selected for this review.

Which settings were represented in the highly cited papers? 37% of the papers listed in Table 2 were based on educational data collected in North America, 31% in Europe, and 11% in Australasia. The remainder of the papers focused on fully online settings in international courses, such as MOOCs. In

63% of the studies, data were collected in higher education settings; 23% in adult learning, professional learning, and MOOC settings; and only 11% in primary and secondary education. In terms of the modality of educational provisions, 63% of the studies examined fully online courses, 26% face-to-face educational settings, and 11% blended settings that required both in-person and online interpersonal learning interactions. Across all highly cited studies, students were treated as network nodes, that is these studies analyzed networks of students. The smallest network comprised 12 students, whereas the largest one included 4,337 students; the mean and median network size across highly cited studies were respectively 511 and 83 students. Two papers did not report the number of students studied. In addition to examining networks of different sizes, in 57% of the studies the networks were collected in one course only; 14% of the studies analyzed student networks in two courses. The remaining studies analyzed program-based networks and alike, with varying numbers of courses.

What theoretical frames were used for the analysis of student networks in highly cited papers? 57% of the papers in the dataset used theory to frame network analysis. 42% of papers did not use theory or only loosely referenced theory without explicitly incorporating its lenses in the analysis or interpretation. Frequently used theoretical frames included 'social capital', 'structural holes', retention, and integration into social structures (e.g. being central to the networks). Studies often applied socio-cultural, socio-technological, and social constructivist perspectives on learning. Studies also had examples of how centrality measures in student networks were interpreted to identify student roles (brokers, gatekeepers, peripheral).

What methodological choices were reported in the highly cited papers? Before reporting methodological approaches in these highly cited papers, it is important to note that around two thirds of the dataset focused on student relations through online communication and the other third examined face-to-face networks. This signifies that in this set of papers, different data sources were used for edge definitions. In particular, most online student networks were operationalized through text-based technology-mediated online events (discussion logs), such as 'replies', 'mentions', 'comments', 'co-occurs with' in the shared online space (such as a discussion thread), and less frequently log events, such as 'follows' and 'reads'. In essence, these data sources were used to create network projections of digital event data. In contrast, networks constructed from face-to-face settings were based on self-reported relational states, such as 'is friends with', 'is knowledgeable', and 'cooperates with'. Multiplex tie definitions (combined relations, such as 'uses the same computer', 'does homework with', 'submitted at the same time') were rare within the set of highly cited studies.

In terms of the direction of ties, 71% of the studies analyzed directed networks. Three studies did not specify whether directed or undirected networks were analyzed. Approximately 6% of studies used different tie definitions to construct several networks for the same actors but of different relations, then analyzing them and comparing to each other. Only 23% of selected papers constructed weighted networks. This finding is important since around two thirds of the studies analyzed online interactions where information about the frequency of exchanges between learners could be easily extracted and may constitute an important element of the analysis. In some studies information about edge weight was not explicit. For instance, the authors would not state if the ties were weighted but then would include weighted degree measure in their analysis. This suggests that networks were, in fact, weighted.

57% of the studies reported descriptive network measures. 82% of the papers calculated centrality measures; only 1 paper stated that these measures were normalized. 69% of the studies analyzed student networks in combination with other data, most commonly text/content sent among students, student grades, and self-reported measures (such as the sense of belonging). Complementary data were used in studies seeking to correlate learning measures with network indices. Some network studies also examined network structures to understand the networks' 'inclusiveness' and 'communication patterns'.

UCINET was predominantly used to calculate measures (given that some papers date back over a decade), but other tools were also used, including R, Gephi, Pajek, State, NodeX, Python-NetworkX, Cytoscape, Meerkat-ed, KBDeX, Netdraw, and NetMiner. However, three studies did not mention the software that was used to calculate the metrics. Given that software packages may use somewhat varied versions of metrics, it is worth noting that only 14% of the papers included equations for the metrics they calculated.

Table 2
Overview of selected studies (citations as in Scopus, April, 2021)

Authors	Title	Venue	Citations
Stewart & Abidi, 2011	Applying social network analysis to understand the knowledge sharing behaviour of practitioners in a clinical online discussion forum	Journal of Medical Internet Research	50
Rabbany, Takaffoli & Zaiane, 2011	Analyzing Participation of Students in Online Courses Using Social Network Analysis Techniques.	Proceedings of educational data mining	50
Vaughan et al., 2015	Bridging the gap: The roles of social capital and ethnicity in medical student achievement	Medical Education	38
Vercellone-Smith, Jablokow, & Friedel, 2012	Characterizing communication networks in a web-based classroom: Cognitive styles and linguistic behavior of self-organizing groups in online discussions	Computers and Education	42
Ryu & Lombardi, 2015	Coding Classroom Interactions for Collective and Individual Engagement	Educational Psychologist	37
Marcos-Garcia, Martinez-Mones, & Dimitriadis, 2015	DESPRO: A method based on roles to provide collaboration analysis support adapted to the participants in CSCL situations	Computers and Education	36
Yang et al., 2015	Group interactive network and behavioral patterns in online english-to-Chinese cooperative translation activity	Internet and Higher Education	34
Thoms & Eryilmaz, 2014	How media choice affects learner interactions in distance learning classes	Computers and Education	61
Xie,Yu, & Bradshaw, 2014	Impacts of role assignment and participation in asynchronous discussions in college-level online classes	Internet and Higher Education	49
Zhang et al., 2017	Interactive networks and social knowledge construction behavioral patterns in primary school teachers' online collaborative learning activities	Computers and Education	42
Oshima, Oshima, & Matsuzawa, 2012	Knowledge Building Discourse Explorer: A social network analysis application for knowledge building discourse	Educational Technology Research and Development	84
Wise & Cui, 2018	Learning communities in the crowd: Characteristics of content related interactions and social relationships in MOOC discussion forums	Computers and Education	36
Shea et al., 2013	Online learner self-regulation: Learning presence viewed through quantitative content- and social network analysis	IRRODL	41
Zheng & Warschauer, 2015	Participation, interaction, and academic achievement in an online discussion environment	Computers and Education	40
Skrypnyk et al., 2015	Roles of course facilitators, learners, and technology in the flow of information of a CMOOC	IRRODL	31
Tirado, Hernando, Aguaded, 2015	The effect of centralization and cohesion on the social construction of knowledge in discussion forums	Interactive Learning Environments	34

Lu & Churchill, 2014	The effect of social interaction on learning engagement in a social networking environment	Interactive Learning Environments	44
Rienties et al. 2012	The role of scaffolding and motivation in CSCL	Computers & Education	76
Rienties & Kinchin, 2014	Understanding (in)formal learning in an academic development programme: A social network perspective	Teaching and Teacher Education	40
Eckles & Stradley, 2012	A social network analysis of student retention using archival data	Social Psychology of Education	35
Kellogg, Booth, & Oliver, 2014	A social network perspective on peer supported learning in MOOCs for educators	IRRODL	67
Hernandez-Garcia et al. 2015	Applying social learning analytics to message boards in online distance learning: A case study	Computers in Human Behavior	60
Gillani & Eynon, 2014	Communication patterns in massively open online courses	Internet and Higher Education	131
Chen et al., 2018	Fostering student engagement in online discussion through social learning analytics	Internet and Higher Education	35
Grunspan et al., 2016	Males' under-estimate academic performance of their female peers in undergraduate biology classrooms	PLoS ONE	91
Dawson, Tan, & McWilliam, 2011	Measuring creative potential: Using social network analysis to monitor a learners' creative capacity	Australasian Journal of Educational Technology	33
Conlan et al., 2011	Measuring social networks in British primary schools through scientific engagement	Proceedings of the Royal Society B: Biological Sciences	41
Fire, 2012	Predicting Student Exam's Scores by Analyzing Social Network Data	Lecture Notes in Computer Science	31
Gasevic, D. et al., 2019	SENS: Network analytics to combine social and cognitive perspectives of collaborative learning	Computers in Human Behavior	50
De-Marcos et al., 2016	Social network analysis of a gamified e-learning course: Small-world phenomenon and network metrics as predictors of academic performance	Computers in Human Behavior	58
Lambropoulos, Faulkner, & Culwin, 2012	Supporting social awareness in collaborative e-learning	British Journal of Educational Technology	44
Bruun & Brewe, 2013	Talking and learning physics: Predicting future grades from network measures and Force Concept Inventory pretest scores	Physical Review Special Topics - Physics Education Research	32
Jimoyiannis, 2012	Towards an analysis framework for investigating students' engagement and learning in educational blogs	Journal of Computer Assisted Learning	38
Joksimovic et al., 2016	Translating network position into performance: Importance of centrality in different network configurations	ACM International Conference Proceeding Series	44
Grunspan, Wiggins, & Goodreau, 2014	Understanding classrooms through social network analysis: A primer for social network analysis in education research	CBE Life Sciences Education	101

5. Workshop Discussion

The presented overview of research settings, theoretical framings, and methodological details in these highly cited studies of student networks suggests limited generalizability of research findings across contexts, given the lack of details needed to understand and interpret the findings. Descriptive measures also lack generalizability, as they are predominantly derived for one or two cases (i.e. one or two networks) and are embedded in a specific pedagogical context. These contexts are not always explicitly described. To open the conversation about how to improve this state of research, the workshop participants, were invited to discuss questions, such as: (1) Are we asking practice-related questions that enable action? (2) Are we asking questions in a way that elicits theoretical insights? (3) Are we reporting our methods in ways that are reproducible? (4) What social science and learning theories apply to socio-technical networks? What measures and interpretations are relevant for socio-technical networks? (5) What recommendations can be provided at this stage to improve the quality of network research in learning analytics? Group notes from discussions are available at the https://learningfutures.github.io/lak-network/.

Much discussion in relation to theoretical issues revolved around the need to understand what elements of social theories (e.g., theories of social capital, social ties, constructs of prestige, power, harmonics) translate to digital settings, and what conceptual and methodological adjustments may be needed to incorporate these theories in studies on digital learning and computer-mediated communication.

Another prominent discussion revolved around the issues of reporting methodological details to ensure both methodological and conceptual rigor.

6. Recommendations

Whereas contributions to theory are beyond the scope of our workshop, suggestions around the reporting of methodological details could be made. To improve the quality and transferability of empirical work focused on the analysis of learning, communication, and social processes in digitally mediated settings, we put forward a set of recommendations applicable to future network research in learning analytics. As researchers working at the intersection of digital data and social networks, we suggest that future studies incorporate the following in their reports.

1) Recommended elements for describing network studies in learning analytics:

- What are the nodes and their relevance to the context, theory, or research question?
- What are the edges, and what do they represent? Are there any assumptions made for the edge definition and what are the justifications for such assumptions?
- Is the network directed, undirected, or mixed?
- Is the network weighted? Is the network simplified or filtered based on a certain threshold? If so, how was the threshold justified?
- How do the edges, weight, and direction align with the context, theory, and interpretation?
- Is the network unipartite or bipartite?
- If edges were aggregated; what was the duration over which the aggregation was made?
- What software, and which version, was used to calculate network indices? What algorithms or equations were implemented in the software to compute these indices?
- What software was used for network visualization? Which network layout was used?
- What community detection method, algorithm, and parameters were used?
- What was the size of the network: number of nodes, edges in each of the studied networks; were there any isolates, were they excluded from the analysis and why?
- In communication networks that are constructed from event data, was time (discrete or continuous) and frequency of exchanges included in the network construction or statistical modelling; if not, why this information was excluded.

- What setting (e.g., learning context, pedagogical design) was the network developed in? How does this setting compare with other reported studies?

2) Additional suggestions for analysis of networks that are in part constructed from digital data:
   - Justify how the findings contribute to theory or address an applied problem. If possible, consider explaining why social network theory is applicable to networks constructed from digital trace events; the use of social science constructs, such as power or influence may not carry its meaning into the digital context, or at least in full, and needs elaboration.
   - If possible, justify the choice of centrality measures and elaborate on the interpretations of centrality measures in digital learning.
   - If relevant, use null models to compare networks or infer if observed structures occurred by chance, rather than draw inferences from descriptive measures between potentially incomparable structures.
   - When modelling networks statistically, include goodness of fit plots for relevant methods.

We hope these recommendations could serve as points of departure for future dialogues that will continue to add to and refine the list. We invite network researchers in learning analytics to join the conversation.

7. Citation Diversity Statement

Recent work in several fields of science has identified a bias in citation practices such that papers from women and other minorities are under-cited relative to the number of such papers in the field (Zurn et al.). We have manually checked the first and the last author's names in the reference list and inferred gender. By this measure, 16% of the cited literature was written by woman (first author)/woman (last author), 16% by men (first)/woman (last), 16% by woman (first)/ man (last), and 50% by man (first)/man (last). This method is limited as it is not indicative of gender identity, and it cannot account for intersex, non-binary, or transgender people. We look forward to future work that could help us to better understand and support equitable practices in science.

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