CS 3891 / 5891 / BMIF 7391 — Special Topics

Network and Graph AI Analysis in Healthcare

Syllabus — Fall 2026 (Tentative)

Instructor	You Chen, Ph.D. (you.chen@vanderbilt.edu)
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Semester	Fall 2026
Time	Tuesday & Thursday, 8:00 – 9:15 am
Location	Featheringill Hall 132
Website	Brightspace (CS 3891)
Office Hours	Upon appointment
Academic session	Aug 26, 2026 – Dec 10, 2026
No classes	Oct 22 (Fall Break); Nov 10 & 12 (AMIA 2026, Dallas, Nov 7–11); Nov 24 & 26 (Thanksgiving)

Description

Network analysis has become a pivotal tool in healthcare, offering powerful methods to extract meaningful insights from vast and complex healthcare data. This course provides an overview of the field from its historical foundations to the current frontier of graph AI — node embeddings, graph neural networks, graph transformers, knowledge graphs with graph-based retrieval-augmented generation (Graph RAG), and biomedical foundation models. It emphasizes perspectives from data mining, machine learning, and statistics, and it grounds every method in real healthcare applications. The course has three components:

- Instructor-led sessions introducing the foundational and modern (graph AI) concepts of network analysis and their relevance to healthcare.
- Student-led presentations on published research, delivered together with the group's initial project proposal.
- Student projects applying network analysis and graph AI to real-world healthcare problems.

The course includes 22 chapters (five parts)*: From Network Analysis to Graph Machine Learning*, which takes students from the mathematical and historical foundations of network analysis through the full arc of graph AI and its healthcare applications.

Objectives

By the end of this course, students will be able to:

- Understand the history and foundational concepts of network analysis, and formalize a healthcare problem as a graph.

- Apply classic network metrics — centrality, community detection, motifs, generative models — and interpret them clinically.
- Apply modern graph AI — node embeddings, graph neural networks, graph transformers, knowledge graphs and Graph RAG, and foundation models — and know when each is appropriate.
- Design and execute a small-scale research project using network analysis and/or graph AI on real healthcare data.
- Reason honestly about the ethics, fairness, privacy, and reproducibility of networked health data and models.

Course Content: The Five Parts

The course is organized into five parts and twenty-two chapters. Part I builds the foundations; Part II covers the classic tools for measuring network structure; Part III develops modern graph AI; Part IV applies both across eight areas of healthcare; and Part V addresses responsible practice. The chapters in each part are listed below.

Part I — Foundations

Chapters 1–4. Why Networks and Graph AI in Healthcare; Graph Theory Foundations; Social Network Analysis — History and Theory; and Network Types and Healthcare Data.

Part II — Classic Network Analysis

Chapters 5–8. Network Metrics and Centrality; Community Detection; Substructures — Motifs, Graphlets, Homophily, and Core–Periphery; and Generative Network Models.

Part III — Graph AI: Machine Learning on Graphs

Chapters 9–13. From Graph Features to Node Embeddings; Graph Neural Networks; Graph Transformers; Knowledge Graphs, LLMs, and Graph RAG; and Foundation Models and Graph AI Agents.

Part IV — Healthcare Applications

Chapters 14–21. Patient-Sharing and Collaboration Networks; Patient-Flow and Care-Transition Networks; Disease, Symptom, and Multimorbidity Networks; Drug Interaction and Pharmacological Networks; Molecular and Biological Networks; Brain Connectomics; Epidemic and Public-Health Networks; and Social Determinants, Equity, and Health-Information Networks.

Part V — Doing It Responsibly

Chapter 22. Ethics, Fairness, and Evaluation.

Prerequisites

There is no official prerequisite. However, students are expected to have proficiency in designing and writing software (Python preferred; any language is acceptable — CS 3270 level), and basic knowledge of statistics (MATH 2820/5820 level). Familiarity with linear algebra and a deep-learning framework (PyTorch) is helpful for the graph-AI portion but is not required.

Course Software and Data

Software: NetworkX (Python) and igraph (R) for classic analysis; Gephi and Cytoscape for visualization; PyTorch Geometric and DGL for graph learning.

Public data: Stanford SNAP and Biomedical Network collections (snap.stanford.edu), PhysioNet, CMS Open Payments, GWAS and PheWAS catalogs, STRING and BioGRID, OpenNeuro and the Virtual Brain (connectomics), and open drug–drug interaction datasets.

Grading

In lieu of a final exam, the grade has **two components**: the individual student-led paper presentation is delivered together with the group's initial project proposal, so that the proposal grows directly out of the papers each member presents. Students work in groups of up to three.

Component 1 — Student-Led Presentation + Initial Proposal (40%)

Each group member presents one published paper, and the group presents its initial project proposal in the same block. The proposal is built from what the members learn in the papers they present. Instructor-led sessions in the first weeks introduce the required concepts so that groups are prepared to propose.

Student-led paper presentation (individual). Duration 12 minutes (10 present, 2 Q&A). Each student presents one article connected to the group's project theme (from the reading list or independently chosen). Required elements:

- **Research question** — what problem is addressed?
- **Data** — type, source, collection, preprocessing.
- **Network construction** — nodes, edges, how relationships are defined.
- **Metrics / methods** — which network measures or graph-AI methods are applied and how they are interpreted.
- **Application** — how the results are used (statistics, visualization, machine learning, prediction).
- **Findings** — the major results.
- **Reflection** — limitations, personal critique, and how the paper informs the group project.

Initial proposal (group). Duration 12 minutes (10 present, 2 Q&A). Should include: title; background and motivation (why the topic matters and why network/graph analysis is essential); hypotheses/goals/research questions; data and study design (data source(s) and summary statistics; network design — ego, whole, directed, two-mode; planned metrics, community-detection or graph-learning methods; tools); and a timeline with milestones.

Component 2 — Course Project (60%)

The project is a semester-long, group-based independent study. It is graded in two milestones after the initial proposal.

Progress report and presentation (20%). Written report and slides. Should include: clear statement of objectives; materials and cohort (dataset(s), description, summary tables); methods (network creation — nodes, edges, weights, directionality; one- vs. two-mode; metrics/graph-learning methods linked to outcomes); preliminary results (early analyses, tables, or visualizations); tools used (NetworkX, Gephi, Cytoscape, PyTorch Geometric, etc.); and challenges encountered with possible solutions. Duration 12 minutes (10 present, 2 Q&A). Each member presents an assigned section.

Final report and presentation (40%). Written report (up to 3,000 words) and slides. Structure: title; structured abstract (≤250 words: objective, materials/methods, results, conclusion); introduction;

materials and methods; results (up to 4 tables and 6 figures); discussion and conclusion; references (no limit). Duration 15 minutes (13 present, 2 Q&A). Each member presents an assigned section.

Grading weights are a recommended default and may be adjusted by the instructor. Collaboration is expected to be balanced: each member must have clear responsibilities across all deliverables.

Key deadlines

- **Group membership + paper list due:** Tue, Sep 22.
- **Written initial proposal (one page) + slides due:** Tue, Oct 6.
- **Presentation + proposal presentations:** Oct 8 – Oct 29 (assigned schedule).
- **Progress report (written) + slides due:** Tue, Nov 3.
- **Progress report presentations:** Nov 5, 17, 19.
- **Final report (≤3,000 words) + slides due:** Mon, Nov 30.
- **Final presentations:** Dec 1, 3, 8, 10.

Topic and Schedule Overview

Twenty-six meeting sessions (Tue/Thu). Instructor-led sessions introduce the required concepts (Parts I–III and responsible use); students then deliver combined paper presentations and proposals, progress reports, and final presentations. Application themes (Part IV) are engaged primarily through the student-led paper presentations.

#	Date	Topic / Activity	Led by
1	Thu Aug 27	Course overview; Ch 1 — Why Networks and Graph AI in Healthcare	Instructor
2	Tue Sep 1	Ch 2 — Graph Theory Foundations	Instructor
3	Thu Sep 3	Ch 3 — Social Network Analysis: History & Theory	Instructor
4	Tue Sep 8	Ch 4 — Network Types & Healthcare Data	Instructor
5	Thu Sep 10	Ch 5 — Network Metrics & Centrality	Instructor
6	Tue Sep 15	Ch 6 — Community Detection	Instructor
7	Thu Sep 17	Ch 7 — Motifs, Graphlets, Homophily, Core–Periphery; Ch 8 — Generative Models	Instructor
8	Tue Sep 22	Ch 9 — Node Embeddings · Groups + paper list due	Instructor
9	Thu Sep 24	Ch 10 — Graph Neural Networks	Instructor
10	Tue Sep 29	Ch 11 — Graph Transformers	Instructor
11	Thu Oct 1	Ch 12 — Knowledge Graphs & Graph RAG; Ch 13 — Foundation Models & Agents	Instructor
12	Tue Oct 6	Part IV applications overview (Ch 14–21); Ch 22 — Ethics, Fairness & Reproducibility; project logistics · Written proposal due	Instructor
13	Thu Oct 8	Student presentation + initial proposal (Group A)	Students
14	Tue Oct 13	Student presentation + initial proposal (Group B)	Students
15	Thu Oct 15	Student presentation + initial proposal (Group C)	Students
16	Tue Oct 20	Student presentation + initial proposal (Group D)	Students
—	Thu Oct 22	No class — Fall Break	—
17	Tue Oct 27	Student presentation + initial proposal (Group E)	Students
18	Thu Oct 29	Student presentation + initial proposal (Group F) / buffer	Students
19	Tue Nov 3	Progress reports (Groups A–B) · Progress report due	Students
20	Thu Nov 5	Progress reports (Groups C–D)	Students
—	Tue Nov 10	No class — AMIA 2026 (Dallas)	—
—	Thu Nov 12	No class — AMIA 2026 (Dallas)	—
21	Tue Nov 17	Progress reports (Groups E–F)	Students
22	Thu Nov 19	Advanced topics / project consultations	Instructor
—	Tue Nov 24	No class — Thanksgiving	—
—	Thu Nov 26	No class — Thanksgiving	—
23	Tue Dec 1	Final presentations (Groups A–B) · Final report due Nov 30	Students
24	Thu Dec 3	Final presentations (Groups C–D)	Students
25	Tue Dec 8	Final presentations (Groups E–F)	Students
26	Thu Dec 10	Final presentations (overflow) & course wrap-up	Students

Group letters are placeholders; the presentation order will be assigned once groups form. If more than six groups enroll, the Oct 29 and Dec 10 buffer sessions absorb the overflow.

Thematic Reading List

Papers are grouped by theme. Each student selects one paper to present (with the group's proposal); groups may draw from one theme or across themes, or use the broader literature. Complete per-chapter reference lists appear in the course text. Following each theme are student project ideas.

Foundational Reviews

[1] Burns LR, Nembhard IM, Shortell SM. Integrating network theory into the study of integrated healthcare. Soc Sci Med. 2022;296:114664.

[2] Borsboom D, Deserno MK, Rhemtulla M, et al. Network analysis of multivariate data in psychological science. Nat Rev Methods Primers. 2021;1:58.

[3] Saatchi AG, Pallotti F, Sullivan P. Network approaches and interventions in healthcare settings: a systematic scoping review. PLoS One. 2023;18(2):e0282050.

[4] Siminea N, Czeizler E, Popescu VB, et al. Connecting the dots: computational network analysis for disease insight and drug repurposing. Curr Opin Struct Biol. 2024;88:102881.

[5] Borgatti SP, Mehra A, Brass DJ, Labianca G. Network analysis in the social sciences. Science. 2009;323(5916):892-895.

[6] Barabási A-L. Network Science. Cambridge University Press, 2016 (freely available online).

Student project ideas: *Review published network/graph-AI studies in one healthcare area to identify common methodologies, data, and gaps that a project could address.*

Theme 1 — Graph AI Methods

[1] Perozzi B, Al-Rfou R, Skiena S. DeepWalk: online learning of social representations. KDD. 2014.

[2] Grover A, Leskovec J. node2vec: scalable feature learning for networks. KDD. 2016.

[3] Kipf TN, Welling M. Semi-supervised classification with graph convolutional networks (GCN). ICLR. 2017.

[4] Hamilton WL, Ying R, Leskovec J. Inductive representation learning on large graphs (GraphSAGE). NeurIPS. 2017.

[5] Veličković P, Cucurull G, Casanova A, et al. Graph attention networks (GAT). ICLR. 2018.

[6] Vaswani A, Shazeer N, Parmar N, et al. Attention is all you need. NeurIPS. 2017.

[7] Ying C, Cai T, Luo S, et al. Do transformers really perform bad for graph representation? (Graphormer). NeurIPS. 2021.

[8] Rampášek L, Galkin M, Dwivedi VP, et al. Recipe for a general, powerful, scalable graph transformer (GPS). NeurIPS. 2022.

[9] Bordes A, Usunier N, Garcia-Durán A, et al. Translating embeddings for modeling multi-relational data (TransE). NeurIPS. 2013.

[10] Lewis P, Perez E, Piktus A, et al. Retrieval-augmented generation for knowledge-intensive NLP tasks. NeurIPS. 2020.

[11] Edge D, Trinh H, Cheng N, et al. From local to global: a Graph RAG approach to query-focused summarization. arXiv:2404.16130. 2024.

[12] Chandak P, Huang K, Zitnik M. Building a knowledge graph to enable precision medicine (PrimeKG). Sci Data. 2023;10:67.

[13] Oss Boll H, Amirahmadi A, Ghazani MM, et al. Graph neural networks for clinical risk prediction based on EHR: a survey. J Biomed Inform. 2024;151:104616.

[14] Bommasani R, Hudson DA, Adeli E, et al. On the opportunities and risks of foundation models. arXiv:2108.07258. 2021.

[15] Moor M, Banerjee O, Abad ZSH, et al. Foundation models for generalist medical artificial intelligence. Nature. 2023;616:259-265.

Student project ideas: *Compare an interpretable metric-based approach with a learned method (node2vec, a GNN, or a graph transformer) on the same healthcare task, reporting accuracy, interpretability, and fairness trade-offs.*

Theme 2 — Professional & Patient-Sharing / Collaboration Networks

[1] Chen Y, Patel MB, McNaughton CD, Malin BA. Interaction patterns of trauma providers are associated with length of stay. J Am Med Inform Assoc. 2018;25(7):790-799.

[2] Yan C, Zhang X, Gao C, et al. Collaboration structures in COVID-19 critical care: retrospective network analysis study. JMIR Hum Factors. 2021;8(1):e25724.

[3] Mannering H, Yan C, Gong Y, et al. Assessing NICU structures and outcomes before and during the COVID-19 pandemic: network analysis study. J Med Internet Res. 2021;23(10):e27261.

[4] Ghomrawi HMK, Funk RJ, Parks ML, et al. Physician referral patterns and racial disparities in total hip replacement: a network analysis approach. PLoS One. 2018;13(2):e0193014.

[5] DuGoff EH, Fernandes-Taylor S, Weissman GE, et al. A scoping review of patient-sharing network studies using administrative data. Transl Behav Med. 2018;8(4):598-625.

[6] Tasselli S. Social networks and inter-professional knowledge transfer: the case of healthcare professionals. Organization Studies. 2015;36(7):841-872.

[7] Yuan CT, Nembhard IM, Kane GC. The influence of peer beliefs on nurses' use of new health IT: a social network analysis. Soc Sci Med. 2020;255:113002.

Student project ideas: *Build a patient-sharing or advice network for a unit or region; detect care teams, find brokers, and relate team structure to an outcome (length of stay, readmission), adjusting for case mix.*

Theme 3 — Patient-Flow & Care-Transition Networks

[1] Lee BY, McGlone SM, Song Y, et al. Social network analysis of patient sharing among hospitals in Orange County, California. Am J Public Health. 2011;101(4):707-713.

[2] Feng Y, Fu J, Patel M, Chen Y. Assessing intrahospital care transition structures before and during the COVID-19 pandemic: network analysis study. AMIA Jt Summits Transl Sci Proc. 2023;2023:148-156.

[3] Bean DM, et al. Network analysis of patient flow in two UK acute care hospitals identifies key sub-networks for A&E performance. PLoS One. 2017;12(10):e0185912.

[4] Ray MJ, Lin MY, Tang AS, et al. Regional spread of carbapenem-resistant Enterobacteriaceae through an ego network of healthcare facilities. Clin Infect Dis. 2018;67(3):407-410.

[5] Cochran JK, Roche KT. A multi-class queuing network analysis methodology for improving hospital emergency department performance. Comput Oper Res. 2009;36(5):1497-1512.

[6] Fonseca BP, Albuquerque PC, Saldanha RF, Zicker F. Geographic accessibility to cancer treatment in Brazil: a network analysis. Lancet Reg Health Am. 2021;7:100153.

Student project ideas: *Model intra-hospital or regional patient flow; locate the min-cut bottleneck or simulate an outbreak spreading through transfers and compare hub-targeted vs. random containment.*

Theme 4 — Disease, Symptom & Multimorbidity Networks

[1] Kalgotra P, Sharda R, Croff JM. Examining health disparities by gender: a multimorbidity network analysis of electronic medical record. Int J Med Inform. 2017;108:22-28.

[2] Carmona-Pírez J, Gimeno-Miguel A, Bliek-Bueno K, et al. Identifying multimorbidity profiles associated with COVID-19 severity using network analysis (PRECOVID). Sci Rep. 2022;12:2831.

[3] Beard C, Millner AJ, Forgeard MJ, et al. Network analysis of depression and anxiety symptom relationships in a psychiatric sample. Psychol Med. 2016;46(16):3359-3369.

[4] Isvoranu AM, Abdin E, Chong SA, et al. Extended network analysis: from psychopathology to chronic illness. BMC Psychiatry. 2021;21:119.

[5] Ljubic B, Gligorijevic D, Gligorijevic J, et al. Social network analysis for better understanding of influenza. J Biomed Inform. 2019;93:103161.

Student project ideas: *Build a chance-adjusted disease co-occurrence network (or a partial-correlation symptom network) and compare its structure across subgroups, or identify central symptoms as treatment targets.*

Theme 5 — Drug & Pharmacological Networks

[1] Jeong E, Malin B, Nelson SD, Su Y, Li L, Chen Y. Revealing the dynamic landscape of drug-drug interactions through network analysis. Front Pharmacol. 2023;14:1211491.

[2] Zhang Y, Yao Q, Yue L, et al. Emerging drug interaction prediction enabled by a flow-based graph neural network with biomedical network. Nat Comput Sci. 2023;3(12):1023-1033.

[3] Udrescu M, Ardelean SM, Udrescu L. The curse and blessing of abundance: the evolution of drug interaction databases and their impact on drug network analysis. Gigascience. 2022;12:giad011.

[4] Cavallo P, Pagano S, Boccia G, et al. Network analysis of drug prescriptions. Pharmacoepidemiol Drug Saf. 2012;21(11):1223-1229.

[5] Hu X, Gallagher M, Loveday W, et al. Network analysis and visualization of opioid prescribing data. IEEE J Biomed Health Inform. 2020;24(5):1447-1455.

Student project ideas: *Build a drug–drug interaction or co-prescription network, identify hub drugs and polypharmacy clusters, or train a link-prediction model to propose undocumented interactions.*

Theme 6 — Molecular & Biological Networks (GNN in Biomedicine)

[1] Huang K, Chandak P, Wang Q, et al. A foundation model for clinician-centered drug repurposing (TxGNN). Nat Med. 2024;30(12):3601-3613.

[2] Donabauer G, Rath A, Caplunik-Pratsch A, et al. A graph-neural-network approach for identifying vancomycin-resistant enterococcus carriers. PLOS Digit Health. 2025;4(4):e0000821.

[3] Zitnik M, Li MM, Wells A, et al. Current and future directions in network biology. Bioinform Adv. 2024.

[4] Oss Boll H, Amirahmadi A, Ghazani MM, et al. Graph neural networks for clinical risk prediction based on EHR: a survey. J Biomed Inform. 2024;151:104616.

Student project ideas: *Detect functional modules in a PPI network, or frame drug repurposing as link prediction on a drug–gene–disease knowledge graph and evaluate top candidates against the literature.*

Theme 7 — Brain Connectomics

[1] Bullmore E, Sporns O. Complex brain networks: graph theoretical analysis of structural and functional systems. Nat Rev Neurosci. 2009;10(3):186-198.

[2] van den Heuvel MP, Sporns O. Rich-club organization of the human connectome. J Neurosci. 2011;31(44):15775-15786.

[3] Fornito A, Zalesky A, Breakspear M. The connectomics of brain disorders. Nat Rev Neurosci. 2015;16(3):159-172.

[4] Li X, Zhou Y, Dvornek N, et al. BrainGNN: interpretable brain graph neural network for fMRI analysis. Med Image Anal. 2021;74:102233.

[5] Kan X, Dai W, Cui H, et al. Brain Network Transformer. NeurIPS. 2022.

Student project ideas: *Build a connectome from public neuroimaging data (OpenNeuro), compare network metrics between groups, or train a graph-classification model for diagnosis with explanations.*

Theme 8 — Epidemic & Public-Health Networks

[1] Pastor-Satorras R, Castellano C, Van Mieghem P, Vespignani A. Epidemic processes in complex networks. Rev Mod Phys. 2015;87(3):925-979.

[2] Christakis NA, Fowler JH. Social network sensors for early detection of contagious outbreaks. PLoS One. 2010;5(9):e12948.

[3] Donabauer G, Rath A, Caplunik-Pratsch A, et al. AI modeling for outbreak prediction: a graph-neural-network approach for VRE carriers. PLOS Digit Health. 2025;4(4):e0000821.

[4] Lee BY, McGlone SM, Song Y, et al. Social network analysis of patient sharing among hospitals in Orange County. Am J Public Health. 2011;101(4):707-713.

Student project ideas: *Simulate SIR/SIS spread on random, scale-free, and small-world networks; compare hub-targeted vs. random vs. friendship-paradox immunization; or model hospital-associated infection.*

Theme 9 — Social Determinants, Equity & Health Information

[1] Christakis NA, Fowler JH. The spread of obesity in a large social network over 32 years. N Engl J Med. 2007;357(4):370-379.

[2] Valente TW. Network interventions. Science. 2012;337(6090):49-53.

[3] Vosoughi S, Roy D, Aral S. The spread of true and false news online. Science. 2018;359(6380):1146-1151.

[4] Gold M, Doreian P, Taylor EF. Understanding a collaborative effort to reduce racial and ethnic disparities in health care: contributions from social network analysis. Soc Sci Med. 2008;67(6):1018-1027.

[5] Holt-Lunstad J, Smith TB, Layton JB. Social relationships and mortality risk: a meta-analytic review. PLoS Med. 2010;7(7):e1000316.

Student project ideas: *Operationalize social isolation as a network metric and relate it to an outcome; audit a bipartite access network for structural disparity; or model health information vs. misinformation diffusion.*

Theme 10 — Ethics, Fairness & Evaluation

[1] Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. Science. 2019;366(6464):447-453.

[2] Chen IY, Pierson E, Rose S, et al. Ethical machine learning in healthcare. Annu Rev Biomed Data Sci. 2021;4:123-144.

[3] Ghassemi M, Oakden-Rayner L, Beam AL. The false hope of current approaches to explainable AI in health care. Lancet Digit Health. 2021;3(11):e745-e750.

[4] Wilkinson MD, Dumontier M, Aalbersberg IJ, et al. The FAIR Guiding Principles for scientific data management and stewardship. Sci Data. 2016;3:160018.

Student project ideas: *Audit a healthcare network model for subgroup fairness and structural disparity, or reproduce a published network result with a full sensitivity analysis.*

This syllabus is tentative and subject to change. Dates follow the Vanderbilt 2026–2027 undergraduate academic calendar; AMIA 2026 is Nov 7–11 in Dallas.