Structural Analysis of the Curriculum Through a Bipartite Network

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Keywords: Bipartite Network, Curriculum, Centrality Analysis, Cognitive Load.

Abstract: Investigation of curriculum elements in terms of knowledge content organisation can be based on two entities that support the process of knowledge acquisition: concepts and learning outcomes. Motivated by this structure of knowledge organisation, we construct curriculum knowledge content as a bipartite network of concepts and learning outcomes. Furthermore, we examine the applicability of centrality estimates in detecting key knowledge entities of curriculum content as well as possibilities to rethink the knowledge organisation and teaching. Results have shown that centrality analysis is particularly suitable for identifying concepts and learning outcomes that are key landmarks for managing cognitive load and improving learning retention.

1 INTRODUCTION

Many real-world systems can be represented as a large collection of interconnected elements, i.e., complex networks. Modelling systems as networks has found its application in transportation and navigation, medicine, criminology, biochemistry, electrical engineering, computer science, operations research, etc. Studies in educational sciences have also shown that network science techniques can reveal the relational nature of knowledge (Siew, 2020).

Knowledge involves the intricate relationships among a set of knowledge elements and is not simply a collection of unrelated facts about a subject.

How knowledge is acquired depends largely on the curriculum model, the role of experts in promoting knowledge acquisition, and the method of information transfer. In this study we examine the quality of design and relevance of outcome-based curriculum, as well as its linkage to effective teaching strategies, learning processes, and information content delivery. Learners are expected to demonstrate mastery of a number of interrelated information, skills, and attitudes within an outcome-based curriculum. Because curriculum plays a crucial role in enabling high-quality learning and in defining and supporting education, curriculum frameworks should cover cross-cutting competencies in addition to subject-specific capabilities.

Consequently, knowledge domains can be perceived as complex systems consisting of clusters and subsystems. Therefore, we opt that the complex nature of educators' knowledge and expertise can be explored through network models and that the structural properties of this knowledge representation can lead to insights. The aim of this paper is to explore the applicability of bipartite network representation to curriculum knowledge design and subdomain recognition. To this end, we construct a bipartite network from the content of IoT educational programme (Veleri – OI IoT School, 2021) and perform an analysis of the corresponding network topology. To the best of our knowledge, this is the first work that shows how to represent and analyse the knowledge organisation of a study programme curriculum as a bipartite network model. Furthermore, we examine the network science approach to curriculum content analysis to answer the following research questions:

RQ1 - Can curriculum knowledge content be modelled through a bipartite network of concepts and learning outcomes?

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Vukic, D., Jakupovic, A. and Candrlic, S.
Structural Analysis of the Curriculum Through a Bipartite Network.
DOI: 10.5220/0011854700003485
In *Proceedings of the 8th International Conference on Complexity, Future Information Systems and Risk (COMPLEXIS 2023)*, pages 53-60
ISBN: 978-989-758-644-6; ISSN: 2184-5034

RQ2 - How can centrality score indicate the key learning outcomes and curriculum knowledge content that can potentially overwhelm working memory and increase cognitive load?

The difficult part in creating a quality curriculum is integrating multidisciplinary in planning, architecture, and design (Centre for teaching excellence, n.d.). There are many design examples where subject content focuses on key knowledge areas but does not reinforce the application of knowledge elements from one subject area to another. Identifying strategies that allow students to develop more consistent thinking patterns across subjects, could support the development of skills, attitudes and values in more than one subject or discipline.

2 RELATED WORK

The application of network science in educational research has found numerous use cases mostly focusing on the study of students' knowledge structure - the internal structure of the conceptual representations that learners acquire, the analysis of social interactions between learners/actors in the educational setting, the quantification of knowledge structures and the uncovering of differences in the structural properties of the knowledge representations of experts and novices, and the conduct of network-based analyses in the context of curriculum design and education (Siew, 2019, 2022; Gera et al., 2021; Kubsch et al., 2020, Koponen & Pehkonen, 2010; O'Meara & Vaidya, 2021; Sun et al., 2020; Ireland & Mouthaan, 2020)

Network structure has also been widely studied in languages, leading to new insights in phonetics, lexical processing, word learning, cognitive science, syntactic structures or learning grammar (Siew & Vitevitch, 2019; Siew, 2022; Castro et al., 2017; Goldstein & Vitevitch, 2017; Hills & Siew, 2018; Citraro et al., 2022; Vitevitch, 2020; Teixeira et al., 2021; Lynn & Bassett, 2020)

Knowledge is often described as a map (diagram), a web, or a network, in which conceptual components are interconnected and form a comprehensive and dynamic system (Novak, 2010; Koponen, 2021; Monahan et al., 2019; Kubsch et al., 2020; Koponen & Nousiainen. 2014; Lynn & Bassett, 2020; Ireland & Mouthaan, 2020) The network science approach aims to model a structure (e.g., a semantic relation) in which nodes (vertices) represent different knowledge elements or concepts and edges (or links) denote a relationship between pairs of concepts (entities or elements).

Educational researchers have long been interested in understanding human cognition - particularly the organization of knowledge, the influence of experience on understanding, and the difference in acquiring expert-like practices and knowledge in a subject area. An increasing number of studies have emphasised the need of shifting from traditional (linear) education to an interconnected model of education that provides a networked (nonlinear) view of knowledge organization (Sun et al., 2020; Siew & Guru, 2022; Gera et al., 2021; Gera et al., 2022)

Understanding the nature of expertise and expert knowledge representations is a crucial task in curriculum development because it greatly influences the effectiveness of instruction and the degree to which "educational engineering" is brought about in the learners.

Furthermore, educational outcomes are expressed through the flow of information and the application of effective instructional techniques that can help students build and organize knowledge structures (Vukić et al., 2020). In addition, curriculum design is complex and should be motivated by the way knowledge is organised, especially in conjunction with educational outcomes for more engaged, longer lasting, and more effective learning.

A fundamental thesis of expertise research is that experts and novices have different representations of knowledge, while experts are able to use their understanding of the deep structure of subject matter to solve a wide range of problems related to their area of expertise (Siew & Guru, 2022).

Researchers emphasise the relevance and usefulness of centrality analysis as a means of quantifying different levels of expertise (Siew & Guru, 2022), identifying key nodes (Lommi & Koponen, 2019; Koponen & Nousiainen, 2019), and measuring the importance of concepts for cohesion (Koponen & Nousiainen, 2014).

O'Meara & Vaidya (2021) explored the role of network theory in an effort to outline meaningful curricular connections and discuss the nature of connectivity in education, illustrated by the example of pre-calculus textbook. Textbooks can be seen as educational repositories of information enabling transfer of expert domain knowledge. The authors emphasise that uncovering an inherently complex nature of connectivity between specific curriculum topics could improve the aggregation of successful curricula across the subject and influence the understanding of scientific concepts and conceptual systems

Vukić et al. (2020) introduced the multidimensional knowledge network (MKN) based on the learning outcomes (Bloom's taxonomy), key concepts in the subject matter domain and the principles of representation and analysis of how domain knowledge (concepts) can be modelled across four levels of knowledge.

Planning, organising and implementing the teaching process requires adopting a multidisciplinary approach. Understanding the nature of domain-specific (or subject-specific) knowledge structures has become an important issue in educational science.

Recent changes due to digitization, networked resources, and interdisciplinary shifts require a rethinking and reconceptualization of knowledge organization. Wheeler (1980) considers two types of relationships between learning experiences: vertical organization of knowledge (concepts learned within one subject area during an academic year) and horizontal organization of knowledge (concepts from one subject are related to concepts in other subjects as an attempt to develop an interrelationship between various subjects or disciplines). According to Thagard (1988) understanding the meaning of a concept's significance comes from its application to different problems and not just from studying its definitions and rules. Therefore, Thagard (1988) emphasizes, concepts need relate to other concepts in ”various inductive, hierarchical, non-definitional ways. This is how meaning emerges.”. Thus, understanding grows as networks expand and connections are strengthened by mutually reinforcing experiences across different subject areas and more tightly structured networks.

In addition, representing concepts and their interrelationships as a complex network is more consistent with our intuition that knowledge is inherently relational in nature, and that expertise is reflected in an interconnected, cohesive organization of concepts in a given domain.

Detecting modules, courses or communities of concepts/learning outcomes, allows for quantitative investigation of relevant knowledge subdomains that may have different properties than the aggregate properties of the network as a whole, e.g., monolayer representation of knowledge organisation in curricula. Informally, a network community is a subgraph whose vertices are more likely to be connected to each other than to vertices outside the subgraph (Barber, 2007).

As mentioned earlier, most network analysis methods and literature refer to unipartite networks, or networks with a single node type. Consequently, it is studied that in process of transformation from bipartite networks into unipartite networks, the loss of information is evident. Bipartite networks have a very particular structure that conflicts with representation in form of square adjacency matrices. In other words, they consist of two different types of nodes, with each edge connecting a node of one type to a node of the other type. In fact, a bipartite network can be used to represent any feature type that can be expressed by a categorical variable. Examples of these categories come from various research areas: scientific publications and authors (Newman, 2001), public transportation routes and stations served (Von Ferber, 2009), food and its ingredients (Ahn et al., 2011), paper and author (Newman, & Park, 2003), article and concept (Palchykov & Holovatch, 2018), etc.

As a case study, Palchykov & Holovatch (2018) uses the structure of concept-related networks of scientific knowledge in the field of physics where they consider a bipartite article-to-concept network with its two one-mode projections as the basic network representation of the publication system. In their research, they have shown how concept features (e.g. subject classes) may be derived from articles and how community detection or clustering approaches may be used to extract groups or modules in such knowledge systems.

3 METHODOLOGY

This paper explores unweighted directed bipartite graph as a formal network representation of the Veleri-OI IoT School international education programme, which is used to identify the desirable design of knowledge organisation. The subject of our analysis was a collection of concepts and learning outcomes from seven modules (courses):

M1. Business idea development
M2. Documentation of user requirements
M3. Setting up a development environment
M4. Non-relational databases
M5. Web application development
M6. Hybrid mobile applications development
M7. Arduino embedded (IoT) systems

In our previous work (Vukic et al., 2023), we defined several steps for data collection and the construction of a monolayer network. Following the defined procedure and the corresponding input data, we extracted unique entities from the aggregated IoT education programme edge list which contains concept pairs and associated learning outcomes. Two types of network nodes were identified from the module curriculum content: concepts and learning outcomes (LO). The semantics of the connection between the nodes is that the concept contributes to the achievement of the learning outcomes.

Accordingly, we created an edge list for the entire IoT education programme - the raw data was modified according to the use case and tool instructions for input data.

In general, bipartite graphs are graphs in which the set of nodes can be partitioned into two disjoint sets such that each edge connects a vertex of one partition to a vertex of the other partition.

The vertex set U has two types of vertices, which represent concepts or LO. Mathematically, $U = A \cup B$ where $A = \{a_1, a_2, ..., a_m\}$ is the set of vertices representing concepts, where m is the number of concepts in this IoT education programme, and $B = \{b_1, b_2, ..., b_n\}$ is the set of vertices representing LO, where n is the number of LO. According to previous studies, three main analytic tasks have been highlighted for this network model (Xu et al., 2014; Yang et al., 2022): i) measuring the importance or role of a node within a given network; ii) identifying clusters of similar elements in one node set in terms of their connections to elements in another node set and vice versa; iii) understanding the connections between clusters in both node sets A and B.

An advantage of this type of network is the ability to quantify the connections between actors and their relationships, rather than relying only on attribute data. In addition, a relational model between entities can be created that provides details about the properties of the network and the interactions of the actors.

Our analysis of the bipartite network of education programme focuses on the topology analysis quantified by the network metrics of degree centrality. Gephi tool was used to visualize and analyse node's centrality for bipartite graph (Bastian et al., 2009)

Exploring node's number of neighbours can be easily done by using degree centrality which simply counts the total number of connections of a node . For a node i, its normalised degree value is given by (Newman, 2018):

$$dc_i = \frac{\sum_{j=1}^{N} K_{ij}}{N-1} \quad (1)$$

where K_{ij} is the ij-th element of the adjacency matrix K of the graph and N is the number of vertices in the graph.

Degree centrality is a useful indicator of a node's total number of connections, but it does not always provide information about a node's importance in terms of linkage to other nodes or its degree of centrality within a larger group (Golbeck, 2013). Although this preliminary research focuses only on the analysis of node centrality and its degree, the importance of nodes in a bipartite network can be investigated using metrics designed specifically for this type of network, which we will discuss in the final chapter of this paper.

4 RESULTS

In this section, we present bipartite representation of the IoT education programme, the application of the defined model to the subject matter area, and the results of the network measures.

4.1 Bipartite Network Representation

The result of the bipartite network representation (RQ1) is partially shown in Figure 1, which demonstrates a bipartite network in which one set of nodes represents concepts from the teaching content (pink) and the other set represents learning outcomes of the teaching content (green) filtered according to the node's degree for the value 13-30 (maximum number of neighbours of the node) i.e. nodes that have between 13 and 30 connections to the nodes are shown. We chose this interval so that we can clearly present the nodes, i.e. two sets of nodes. The semantics of the connection between nodes is that the concept contributes to the achievement of learning outcomes.

Table 1: Example of data input for bipartite network.

LO	Concepts
M2.I1.1.describe the phases of requirements management	user needs user requirement user requirement analysis **requirements management** system requirements requirements management requirement elicitation requirement specification requirement validation requirement negotiation
M5.I3.3. Ensure access to web services by creating routes	creating a route HTTP protocol REST Node.js Express JavaScript **requirements management** HTTP protocol API call REST architecture

Table 1 shows an example of data input for bipartite network pairing the learning outcome node type with the concept node type concept. Based on these two rows, two nodes of the learning outcome type would be created: M2.I1.1. Describe the phases of requirements management and M5.I3.3. Ensure access to web services by creating routes that are connected to ten Concept type nodes from the corresponding line.

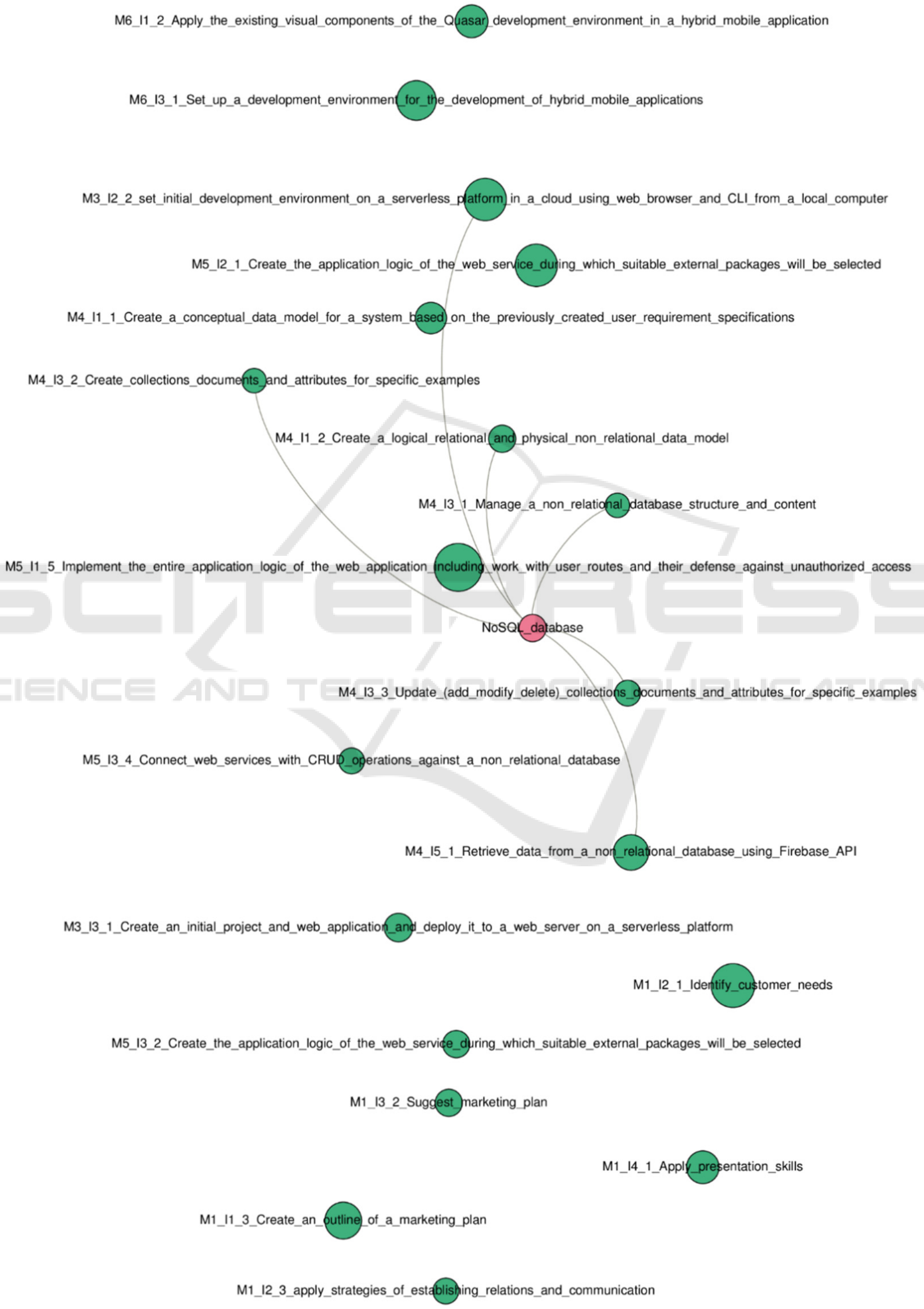

Figure 1: Bipartite network representation of the IoT education programme.

Also, it is evident that among these 10 concepts is a concept: requirements management which is a link to both learning outcomes mentioned above.

4.2 Bipartite Network Analysis

Table 2 presents the results of the global characterization of the structural properties for the bipartite network of the IoT programme: total number of learning outcomes (LO), total number of identified concepts (C) and total number of edges (E). Furthermore, we explore top five nodes from each set in terms of the number of neighbours they are connected to.

Table 2: Basic characteristics of the dataset

Bipartite network	LO	C	E
IoT education programme	112	399	799

The subject of our analysis was a collection of LO and concepts listed in the Veleri-OI IoT School international education programme module's curriculum. The curriculum contains 511 unique nodes. 112 of these nodes are learning outcomes and 399 are concepts.

Exploration of the module networks shows variations in the number of nodes from network sets. In other words, the learning outcome set has a significantly smaller number of nodes.

Table 3: The top five ranked nodes by degree (dc_i) for node type: concept.

Concept	dc_i
NoSQL database	15
client server architecture	9
database	9
HTTP protocol	9
Firestore	9

The degree of a node represents the largest number of connections (neighbours) that a node has in the network. Figure 1 presents nodes filtered by range of degree 13-30. If a concept node is connected with multiple links to different sets of LO, it means that this concept contributes to different learning outcomes at the level of the teaching unit.

Table 4: The top five ranked nodes by degree (dc_i) for node type: learning outcome.

Learning outcomes	dc_i
M5.I1.5 Implement the entire application logic of the web application including work with user routes and their defense against unauthorized access	30
M1.I2.1 Identify customer needs	27
M3.I2.2 set initial development environment on a serverless platform in a cloud using web browser and CLI from a local computer	26
M5.I2.1 Create the application logic of the web service during which suitable external packages will be selected	26
M6.I3.1 Set up a development environment for the development of hybrid mobile applications	24

For example, the concept NoSQL database (Table 3) is associated with a large number of outcomes and contributes to the achievement of multiple learning outcomes. The centrality analysis shows that this concept can be crucial in integrating a multidisciplinary study that allows students to develop important transferable skills such as critical thinking and synthesis of ideas. Therefore, it can be concluded that revisiting key concepts across multiple learning outcomes may increase the likelihood of retaining knowledge in a student's long-term memory and improve learning retention (RQ2). In addition, the LO node M5.I1.5 Implement the entire application logic of the web application including work with user routes and their defense against unauthorized access (Table 4) which has a degree value of 30 represents a learning outcome to which 30 different concepts contribute. Using this network approach we can determine the complexity of LO based on the number of concepts that contribute to this outcome.

Expert knowledge reflects structured, intricately interwoven cognitive schemas that include one's knowledge and abilities and are a necessary component of a well-organized long-term memory. Knowledge organisation which supports a reduction in cognitive load during learning and problem solving, leads to increased competence. Processing new information results in "cognitive load" on working memory and can affect learning outcomes (Kalaš, & Mittermeir, 2011). Overload occurs in learning settings where a large number of items are thought of at once. For any outcome with a large number of concepts, educators should consider decomposing learning outcomes into less cognitively complex learning outcomes or systematically organising knowledge content (concepts) to facilitate complex learning.

5 CONCLUSIONS

The essential role of curriculum is to enable quality learning and to provide a foundational framework for achieving high-quality learning outcomes. The curriculum as a complex network consists of several types of elements and exhibits multiple relations between them, which is emphasised by the fact that the node objects are heterogeneous and the edge types are diverse. Acknowledging the multivariate nature of the network, we move from the simple monolayer representation to a more powerful abstraction for modelling – the bipartite network model. Hence, we extract entities from the curriculum knowledge content - concepts and LO into two sets and construct an unweighted directed bipartite network (RQ1). To demonstrate and apply relationships between related subjects, learning processes should enable students to draw meaningful connections between subjects and integrate multiple subjects into larger learning domains. As a result, it would also encourage the growth of more intricate cognitive interconnections and structures, and consequently, of competences and skills within and across domains. Centrality analysis has shown that achieving the learning outcomes with large number of concepts is highly correlated with cognitive load during learning of new and yet strongly interwoven concepts (RQ2). Measuring the importance of nodes in bipartite graphs could be easily bypassed by projecting the bipartite graph onto a unipartite network and calculating the centrality values using, for example, the PageRank or Eigenvector centrality algorithms, which may lead to information loss and distortion of the network topology, resulting in misleading results. Therefore, in our future work, we will investigate centrality metrics designed specifically for bipartite networks - BiRank, HITS, CoHITS and BGRM centrality index and their comparison with unipartite network model for the IoT education programme. The representation of knowledge networks as bipartite network, apart from enabling the key entity detection, allows the study of the effective knowledge organisation, in terms of optimal information transfer that student can absorb and retain effectively provided in such a way that it does not "overload" their mental capacity.

ACKNOWLEDGEMENTS

This work has been fully supported by the University of Rijeka under the project number uniri-drustv-18-140.

REFERENCES

Ahn, Y. Y., Ahnert, S. E., Bagrow, J. P., & Barabási, A. L. (2011). Flavor network and the principles of food pairing. Scientific reports, 1(1), 1-7.

Barber, M. J. (2007). Modularity and community detection in bipartite networks. Physical Review E, 76(6), 066102.

Bastian, M., Heymann, S., & Jacomy, M. (2009, March). Gephi: an open source software for exploring and manipulating networks. In Proceedings of the international AAAI conference on web and social media (Vol. 3, No. 1, pp. 361-362).

Castro, N., Pelczarski, K. M., & Vitevitch, M. S. (2017). Using network science measures to predict the lexical decision performance of adults who stutter. Journal of Speech, Language, and Hearing Research, 60(7), 1911-1918.

Centre for teaching excellence (n.d.). Forming a program's structure, https://uwaterloo.ca/centre-for-teaching-excellence/forming-programs-structure

Citraro, S., Vitevitch, M. S., Stella, M., & Rossetti, G. (2022). Feature-rich multiplex lexical networks reveal mental strategies of early language learning. arXiv preprint arXiv:2201.05061.

Gera, R., BartoIf, D. M., Isenhour, M. L., & Tick, S. (2019). Chunk: Curated heuristic using a network of knowledge.

Gera, R., Saxena, A., Bartolf, D. M., & Tick, S. (2021). A Network Science Perspective to Personalized Learning. arXiv preprint arXiv:2111.01321.

Golbeck, J. (2013). Network structure and measures. Analyzing the social web, 25-44.

Goldstein, R., & Vitevitch, M. S. (2017). The influence of closeness centrality on lexical processing. Frontiers in psychology, 8, 1683.

Hills, T. T., & Siew, C. S. (2018). Filling gaps in early word learning. Nature Human Behaviour, 2(9), 622-623.

Ireland, J., & Mouthaan, M. (2020). Perspectives on Curriculum Design: Comparing the Spiral and the Network Models. Research Matters.

Kalaš, I., & Mittermeir, R. T. (2011). Informatics in Schools. Contributing to 21st Century Education: 5th International Conference on Informatics in Schools: Situation, Evolution and Perspectives, ISSEP 2011, Bratislava, Slovakia, October 26-29, 2011. Proceedings. Springer.

Koponen, I. T. (2021). Systemic states of spreading activation in describing associative knowledge networks II: generalisations with fractional graph Laplacians and q-adjacency kernels. Systems, 9(2), 22.

Koponen, I. T., & Nousiainen, M. (2014). Concept networks in learning: Finding key concepts in learners' representations of the interlinked structure of scientific knowledge. Journal of Complex Networks, 2(2), 187-202.

Koponen, I. T., & Nousiainen, M. (2019). Pre-service teachers' knowledge of relational structure of physics concepts: finding key concepts of electricity and magnetism. Education Sciences, 9(1), 18.

Koponen, I. T., & Pehkonen, M. (2010). Coherent knowledge structures of physics represented as concept networks in teacher education. Science & Education, 19(3), 259-282.

Kubsch, M., Touitou, I., Nordine, J., Fortus, D., Neumann, K., & Krajcik, J. (2020). Transferring knowledge in a knowledge-in-use task—investigating the role of knowledge organization. Education Sciences, 10(1), 20.

Lommi, H., & Koponen, I. T. (2019). Network cartography of university students' knowledge landscapes about the history of science: landmarks and thematic communities. Applied network science, 4(1), 1-24.

Lynn, C. W., & Bassett, D. S. (2020). How humans learn and represent networks. Proceedings of the National Academy of Sciences, 117(47), 29407-29415.

Monahan, C., Munakata, M., & Vaidya, A. (2019). Creativity as an emergent property of complex educational system. Northeast Journal of Complex Systems (NEJCS), 1(1), 4.

Newman, M. E. (2001). The structure of scientific collaboration networks. Proceedings of the national academy of sciences, 98(2), 404-409.

Newman, M. E. (2018). Networks. Oxford university press.

Newman, M. E., & Park, J. (2003). Why social networks are different from other types of networks. Physical review E, 68(3), 036122.

Novak, J. D. (2010). Learning, creating, and using knowledge: Concept maps as facilitative tools in schools and corporations. Routledge.

O'Meara, J., & Vaidya, A. (2021). A Network Theory Approach to Curriculum Design. Entropy, 23(10), 1346.

Palchykov, V., & Holovatch, Y. (2018, August). Bipartite graph analysis as an alternative to reveal clusterization in complex systems. In 2018 IEEE Second International Conference on Data Stream Mining & Processing (DSMP) (pp. 84-87). IEEE.

Siew, C. S. (2019). Using network science to analyze concept maps of psychology undergraduates. Applied Cognitive Psychology, 33(4), 662-668.

Siew, C. S. (2020). Applications of network science to education research: Quantifying knowledge and the development of expertise through network analysis. Education Sciences, 10(4), 101.

Siew, C. S. (2022). Investigating cognitive network models of learners' knowledge representations. Journal of Learning Analytics, 9(1), 120-129.

Siew, C. S., & Guru, A. (2022). Investigating the network structure of domain-specific knowledge using the semantic fluency task. Memory & Cognition, 1-24.

Siew, C. S., & Vitevitch, M. S. (2019). The phonographic language network: Using network science to investigate the phonological and orthographic similarity structure of language. Journal of Experimental Psychology: General, 148(3), 475.

Sun, H., Yen, P., Cheong, S. A., Koh, E., Kwek, D., & Tan, J. P. L. (2020). Network science approaches to education research. Int. J. Complex. Educ, 1, 122-149.

Teixeira, A. S., Talaga, S., Swanson, T. J., & Stella, M. (2021). Revealing semantic and emotional structure of suicide notes with cognitive network science. Scientific reports, 11(1), 1-15.

Thagard P (1988) Computational Philosophy of Science. The MIT Press, Cambridge, Massachusetts

Veleri – OI IoT School (2021). Polytechnic of Rijeka and the University of Rijeka, Department of Informatics, Development of the International Education Program. https://iot-school.veleri.hr/en/home

Vitevitch, M. S. (Ed.). (2020). Network science in cognitive psychology. Routledge, Taylor & Francis Group.

Von Ferber, C., Holovatch, T., Holovatch, Y., & Palchykov, V. (2009). Public transport networks: empirical analysis and modeling. The European Physical Journal B, 68(2), 261-275.

Vukic, D., Candrlic, S., & Jakupovic, A. (2023). Monolayer network representation and analysis of the curriculum. Computing Conference, (Accepted for publication).

Vukić, Đ., Martinčić-Ipšić, S., & Meštrović, A. (2020). Structural analysis of factual, conceptual, procedural, and metacognitive knowledge in a multidimensional knowledge network. *Complexity*, *2020*, 1-17.

Wheeler, D. K. (1980). Curriculum process. London: Hodder and Stoughton Ltd

Xu, K., Wang, F., & Gu, L. (2013). Behavior analysis of internet traffic via bipartite graphs and one-mode projections. IEEE/ACM Transactions on Networking, 22(3), 931-942.

Yang, K. C., Aronson, B., Odabas, M., Ahn, Y. Y., & Perry, B. L. (2022). Comparing measures of centrality in bipartite patient-prescriber networks: A study of drug seeking for opioid analgesics. PloS one, 17(8), e0273569.