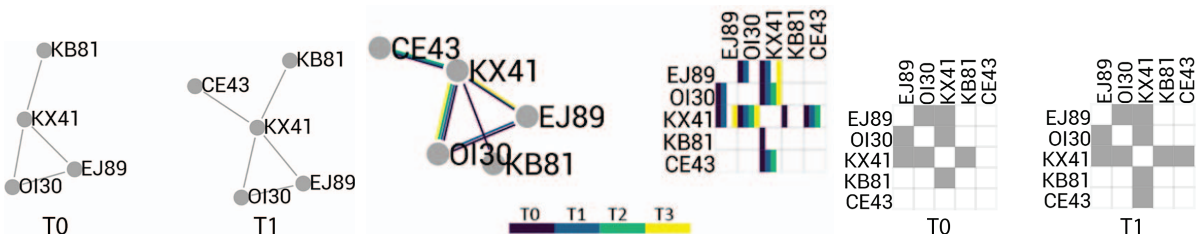
2021 IEEE 14th Pacific Visualization Symposium (PacificVis)

Exploratory User Study on Graph Temporal Encodings

Velitchko Filipov* Alessio Arleo* Silvia Miksch*

TU Wien



(a) Node-Link Juxtaposition (b) Superimposition, Node-Link (left) and Matrix (right) (c) Matrix Juxtaposition

Figure 1: Different combinations of structural and temporal encodings of a network as depicted in our study.

ABSTRACT

A temporal graph stores and reflects temporal information associated with its entities and relationships. Such graphs can be utilized to model a broad variety of problems in a multitude of domains. Researchers from different fields of expertise are increasingly applying graph visualization and analysis to explore unknown phenomena, complex emerging structures, and changes occurring over time in their data. While several empirical studies evaluate the benefits and drawbacks of different network representations, visualizing the temporal dimension in graphs still presents an open challenge. In this paper we propose an exploratory user study with the aim of evaluating different combinations of graph representations, namely node-link and adjacency matrix, and temporal encodings, such as superimposition, juxtaposition and animation, on typical temporal tasks. The study participants expressed positive feedback toward matrix representations, with generally quicker and more accurate responses than with the node-link representation.

Index Terms: Human-centered computing—Visualization—Empirical studies in visualization;

1 INTRODUCTION

A graph is a data structure composed by a set of entities, the "nodes", and their relationships, the "edges". Temporal graphs, also referred to as dynamic networks, are a special case of graphs that store temporal information as changes to the graph's structure. Networks can be used to model a wide range of problems in multiple domains, including sociology [21], epidemiology [28], and software engineering [10]. Approaches to visualize networks in literature are predominantly based on 2D node-link representations or variations thereof, although the use of adjacency matrices to depict relational information is also quite common. After the turn of the millennium, with the larger availability of time-varying datasets, dynamic graph visualization became an established visualization discipline [6], with more techniques being developed and published on this topic. These can be broadly categorized in *timeline* (mapping "time to space") and *animation* (mapping "time to time") approaches [6].

*e-mail: {velitchko.filipov|alessio.arleo|silvia.miksch}@tuwien.ac.at

Kerracher et al. [17] identify the graph structural and graph temporal encoding as the two independent dimensions which can be used to create a design space for temporal graph visualization. Existing studies focus on evaluating which form of temporal encoding to use given a fixed graph structural representation [3, 5, 9, 11, 26] (e.g., animation vs. timeline for node-link representations).

Evaluating the two dimensions independently on temporal graph tasks appears to be an under-investigated area in related literature. However, insights about the performance and the user preference of each combination would be advantageous when designing dynamic graph visualizations and would set the base for further exploration of the design space. Within this context and motivation, in this paper we conduct an exploratory user study with the aim of obtaining insights on how different combinations of temporal encodings and graph representations perform on typical graph temporal tasks (in terms of correctness and response times). We complement our findings with the participants' personal feedback and preferences for each approach to provide a qualitative aspect additional to the quantitative results we obtain from the study. Our main contributions in this paper are: (i) an exploratory user study on graph temporal encodings applied to node-link and adjacency matrix representations; (ii) an analysis of the study results including users' feedback and preference, with a resulting set of insights to drive the formulation of new hypotheses.

2 RELATED WORK

Dynamic network visualization represents the changes to a graph's structure and/or the properties of entities and their relationships over time. The challenge is associated with portraying these changes in an aesthetically pleasing, easily recognizable, and effective manner. In a recent survey on dynamic network visualization [6], the authors categorize approaches according to their visual representation, the encoding of the temporal dimension, and type of evaluation that was conducted. In this paper the authors outline the need for more evaluations in this field of research and summarize that most approaches focus on animated node-link diagrams, with some including timelines, while matrix representations have not been evaluated as extensively in the context of dynamic graph visualization.

Evaluating graph representations. Evaluations of graph visualization techniques in literature aim at assessing the readability of the layout as well as determining which aesthetic criteria affect the human cognition. Purchase et al. [24, 25] focus on the aesthetics of

2165-8773/21/$31.00 ©2021 IEEE
DOI 10.1109/PacificVis52677.2021.00025

graph layouts for node-link representations and report the effect they have on the user's perception of the graph. Bennet et al. [7] further investigate how these aesthetic criteria improve the graph's readability by examining their perceptual basis and evaluation in literature. Ghoniem et al. [14] evaluate the readability of node-link and matrix representations for generic graph related tasks. They conclude that matrix representations have unexplored potential and outline this as future work. Keller et al. [16] evaluate the suitability of matrix and node-link graph representations but differently than previous studies the authors use directed graphs as their data to simulate real-world semantics. Okoe et al. [22, 23] investigate further comparative evaluations between node-link and matrix representations by measuring their performance and accuracy in a user study using large graphs. The authors conclude that overall node-link representations perform better for visualizing large graphs compared to their matrix counterpart. Donghao et al. [27] perform a large scale user study and evaluate the graphical representations of node-link and matrix diagrams for structural tasks, such as, adjacency, accessibility, and connectivity. The authors conclude that node-link representations produce a better implicit understanding of the graph and have higher response accuracy and faster completion times than matrices.

Graph temporal encodings. In dynamic graph visualization the temporal dimension plays a crucial role and requires specific visual and analytical attention to provide effective exploration [20]. The most common techniques to portray the dynamics of networks are animation and small multiples. Animation has proven to be a technique that improves a user's ability to reconstruct the information space effectively and has since been applied to network visualization for conveying a graph's dynamics [4]. Empirical studies from literature evaluate the differences between animated and static visualizations focusing on the effect of mental map preservation for node-link representations [3, 4, 12]. Ghani et al. [13] study the impact of different metrics for dynamic graph visualization on the user's perception of animated node-link diagrams to relay temporal information.

In our survey of related literature, we found a lack of user studies that evaluate the performance of temporal encodings across different graph representations. In this paper, we take a step in this direction with an exploratory within-subject user study evaluating different approaches for representing a network and its temporal dimension on typical graph temporal tasks.

3 User Study

We evaluate three temporal encodings, namely ***Juxtaposition*** (JP), ***Superimposition*** (SI), and ***Animation*** (AN) for ***Node-Link*** (NL) diagrams and ***Adjacency Matrices*** (M). We structure our evaluation as a within-subject user study with the purpose of obtaining insights on the participants' experience with different combinations of temporal encodings and graph representations when facing typical temporal tasks. As in the definition of an exploratory study, our main goal is to gather and report findings that could pave the way to formulate more elaborate hypotheses to be evaluated in future research.

In the following, we outline the design of our user study. Exhaustive data about the survey design and results are available online[1].

Tasks. To elaborate our tasks, we refer to the task taxonomy by Ahn et al. [1], with particular focus on two aspects: the rate of changes and individual temporal features. Our tasks are related to individual entities, such as nodes and links, rather than higher level entities such as groups, clusters, or entire networks. We aim at breaking-down the user exploration with these tasks as to precisely measure their accuracy and completion times. The tasks are the following: (**Q1**) "After investigating the whole sequence, how did the number of edges change from T0 to T3?"; (**Q2**) "After investigating the evolution carefully from start to finish, how did the degree (i.e., the number of neighbors) of a given node change?"; (**Q3**) "After investigating the evolution carefully, in which frame was the relationship between a source node and a target node first introduced?". The requested nodes in the tasks are not highlighted or explicitly labeled; the participants are asked to find these nodes in the graph and track them to count and observe the changes occurring to them. In each task, we request the participants to accurately count the changes and do not ask for general approximations (e.g., estimate if and by how much a nodes degree has increased or decreased over time). The graph size was chosen so that giving a precise answer would be manageable in the context of the experiment.

Graph Representations. We focus on two representations (see Fig. 1). NL diagrams visualize a network using circles for the nodes, with straight lines connecting them to represent their edges. The drawing is laid out on a 2D plane, and the coordinates of the vertices are computed by the standard force-directed layout algorithm from *d3js* [8]. Text labels are shown close to the nodes to identify them. M visualizes a graph as a $n \times n$ matrix, where n is the number of vertices. A non-zero value in cells indicates that there exists an edge between the nodes. Vertices are ordered in rows/columns according to their order of appearance in the source file.

Temporal Encodings. JP represents the temporal dimension as time slices, with each depicting the state of the network at a single point in time (see Fig. 1a and 1c). The time slices are then arranged in a side-by-side manner as to allow for comparison of the network between time steps. We implement this by creating a diagram of each time step for the respective network representation and align those in a side-by-side manner. SI encodes the temporal dimension in the same screen space by overlaying the different time steps on top of each other or by explicitly encoding time using a visual variable. For the evaluation we generate the figures by explicitly encoding the temporal information for M and NL representations using color-coding for the different time steps and overlaying them as seen in Fig. 1b. For M we subdivide each cell uniformly into bars each one representing one time step. For NL we encode time in parallel edges between nodes, each being color-coded according to the time step they occur in. This approach is similar to the technique introduced by Vogogias et al. [29] for visualizing multiple edge types in adjacency matrices and extended for NL. AN depicts the change of the graph over time as smooth transitions between different time steps. For our user study we create animated diagrams, where the changes are represented as layout transitions between subsequent time steps for both the M and NL representations.

As a final remark, we do not include any mental map preservation techniques for the generation of the NL layouts, as we want to compare the implementations of the proposed encodings without any configuration or modification. We believe that including more advanced techniques for layout refinement would influence the perception and performance of some approaches compared to others. Similarly, we do not apply any reordering of the matrix rows/columns and we also restrict the participants interactions (i.e., play-pause buttons) in AN, as any of these could provide some combinations of temporal encodings and graph representations with a significant advantage.

Study Design. We structure our exploratory user study as an online survey. The survey contains a total of 18 questions: in each one of them, a graph is portrayed either as NL or M and the participant has to observe the evolution of a graph, portrayed by one of the experiment's temporal encodings, and solve a task. For each question, we measure the participant accuracy (i.e., absolute value of the difference between the given and the correct answer) and response time. The survey is split in two sections with 9 questions each: in the first one, graphs are represented using NL and in the second using M representation. To mitigate any order effect, in each section we permutate the tasks and temporal encodings following a Graeco-Latin square design on these two factors. At the end, the participant is asked to express their opinion on each different combi-

[1] `https://osf.io/t9uqj/`

nation of graph representation and temporal encoding using a five point Likert scale [19], rating each technique from 1 (least preferred) to 5 (most preferred). The user feedback may also include textual comments pertaining to their experience. The survey has been online and available for 21 days.

Data. We generate 9 scale-free random graphs (one per each combination of task and temporal encoding) using the NetworkX library [15], with 30 vertices and edges ranging from 44 up to 69, comparable to the size of graphs used in similar studies [30]. We choose scale-free graphs to provide a use-case scenario with a realistic node degree distribution, since such graphs encapsulate the characteristics of many real-world networks of scientific interest [2]. For each graph we sample four time steps and model the dynamics of the network as node removal and addition. We generate each time step as follows: we iterate over the entire set of nodes, with each node having a 5% probability of being marked for removal. The edges incident to the marked nodes are removed as well.

Participants. The study was conducted as an optional assignment to a graduate visualization design class through the university's online teaching portal. This course is intended for bachelor students that are fairly advanced in their studies and all participants were familiar with the preliminary concepts required to fulfill the study (i.e., graph representations, temporal encodings). A set of introductory slides was provided, containing a detailed description of the tasks and instructions on how to complete the survey.

4 Results

We received 39 valid surveys, after removal of incomplete or invalid submissions. The absolute error of the participants' responses is shown in Fig. 2; the error rate (i.e., the ratio between wrong and correct answers) is presented for each task in the following discussion. We report the response times in Fig. 3. We report the average value of the participants' preference for each combination of graph representation and temporal encoding in Fig. 4. During the discussion, we report in brackets relevant quotes from the participants' feedback. The first insight that emerges from our results is that M has overall lower and more narrowly distributed response times, especially in **Q1**, compared to the NL representation. We argue this to be due to the intrinsic shortcomings of NL: edge crossings, clutter (e.g., label overlaps), and occlusion played against the participants, making it more difficult for them to formulate an answer to the task. We might infer from the users' feedback that the participants experienced impatience and frustration while solving tasks with the NL representation, which, as we will describe in the following, impacted accuracy as well. Our findings seem contradictory to the results of previous studies that compare M and NL representations [16, 22, 23, 27]. In this regard, we would like to remark that we compare NL and M approaches for temporal tasks and not topology-related tasks (i.e., path-finding), where NL-based approaches have a clear advantage.

Q1. In this task, the participants had to sum up the positive and negative changes of the number of edges for *each* time frame, and this proved to be the most error-prone and time consuming task. Regardless of the representation, the participants' responses are spread across a large interval, with higher error rates and generally longer recorded response times than the other tasks. Concerning NL, JP performs poorly, with none of the participants providing the correct value. We argue that this might be due to a cluttered and hard to read layout, and continuously switching back and forth between time slices caused some difficulties for the participants ("*You had to be very meticulous when comparing the different frames* [...] *the densely packed node clusters made it very easy to miss a vertex entirely.*"). SI and AN perform similarly in terms of error rate (95% and 92% respectively). In AN the median value of the absolute error is the closest to zero. AN also scores the lowest median response time. We conjecture that the changes in the layout caught the attention of the participants making it easier to follow and track them ("*It felt like less information was displayed at a time, which was easier to follow.*"). SI scores in between JP and AN for both time and accuracy: we argue that integrating the temporal information in a single picture made the task somewhat easier on the participants, but visual artifacts due to the parallel edges still caused a high error rate and a larger spread in the responses ("*It is hard to figure out the right ones if the coloured lines are stuffed closely side-by-side*"). Generally, in solving this task with NL, several participants expressed frustration due to the instability of the layout ("*The hardest one to comprehend due to the relative positions of the nodes changing between the individual frames of the transformation*"), possibly due to the lack of mental-map preservation techniques. Concerning M, the trend in the response times is similar to the one found in NL. JP has the highest response time, followed by SI and AN. While the three perform the same in terms of error rate (89%), SI shows a much larger spread in the participants' responses. We argue that in M users might have found difficult to properly interpret the time encoding, possibly leading to double counting each change ("*[In M] the same information is shown twice (which probably not everybody realized at first).*"). Despite the absolute error of M being spread on larger intervals than NL in all **Q1** instances, the median value is inferior on JP and similar to AN.

Q2. This task proved to be easier to solve than **Q1**, with the participants' answers generally distributed over a smaller interval and centered closer to the correct solution. We recorded reduced average response times than **Q1** across all graph representations and temporal encodings. In NL, SI obtains the lowest error rate (48%). We believe this is due to the encoding of the temporal information on the edges of a single layout. SI, however, also has longer response times than JP and AN; we argue this is caused by the readability issues of the temporal encoding ("*It is very difficult to comprehend the clustered information, which sometimes overlaps with each other.*"). Layout instability might be the cause of the higher error rates in AN (95%) and JP (79%): the participants had to continuously look for the node of interest in the layout, which could change its position in subsequent time steps. The high error rate present in JP was not expected, since the participants had all the time slices of the network side-by-side, and we assumed this would make the task easier compared to other temporal encodings. The low spread of the participants' answers suggests that the requested node was placed in a position in which it was difficult to track all of its neighbours unambiguously, deceiving many users in choosing a wrong answer (even if not by much). For M, JP and SI perform similarly in terms of both response times and accuracy, with AN having higher error rates (15%, 10%, and 56% respectively).

Q3. Participants found this task the easiest to solve. For NL, the three temporal encodings perform similarly in terms of error rate, with SI scoring slightly worse (3% for AN, 5% for JP, and 8% for SI) and having the longest response times of the three. We suggest that the visual artifacts generated by the parallel edges had a worse impact than the instability of the layout between subsequent time steps (JP) and the lack of playback controls (AN). Conversely, in M representation, since the vertex order did not change between timestamps, the task was much easier than NL. SI has slightly higher error rates compared to JP (10% and 3% respectively). All participants answers were correct for AN temporal encoding: once the requested cell was located, participants only had to wait for it to fill ("*You have to focus just on the filled rectangles*"). In terms of response times, the three approaches show a similar trend.

User Feedback and Preferences. In Fig. 4 we display the participants' ratings we collected after the study. The results suggest that M collected the favour of the study participants. Their personal preferences remain consistent between network structural representations. The relative differences between JP, SI, and AN are similar for both NL and M representations (i.e., SI obtains the highest scores, followed by JP and AN). This suggests that the representation of the graph does not affect the participants' preferences over the temporal encodings. According to the feedback, AN scores the worst because it was deemed too quick to follow and the absence of any playback controls made it difficult to accurately identify and follow changes. The participants gave JP better scores than AN, but it appears that "*Constantly switching back and forth between the images and comparing only characters/numbers was exhausting.*". However, there was also a fair share of positive arguments, with JP being the encoding of choice for many participants. SI was the most preferred encoding by the study participants, with SI for M scoring the highest among all combinations of temporal encoding and graph representations. We believe that the combination of an adjacency matrix with all the temporal information packed together and integrated in the same view (therefore avoiding the need of navigating back and forth between subsequent time steps) was the most efficient ("[...] *made the counting systematic and therefore easy*"). The SI encoding for NL representations scores higher than the other temporal encodings but the participants felt it "*overwhelming*". The explicit time encoding for this graph representation results in clutter, which in turn makes the colors more difficult to read ("*The lines weren't thick enough to distinguish similar colors.*").

Limitations. In this section we discuss the limitations of our exploratory user study. First and foremost, we do not present a statistical analysis of the results. As in the definition of exploratory studies, we do not have hypotheses to confirm, and therefore such analysis would not have added significant value to the results discussion. We remark that our observations represent empirical evidence aimed at obtaining a broader understanding of the problem, not leading to a conclusive result that would necessitate formal evaluation and statistical testing.

As we state as part of the study design, we do not include any mental map preservation technique, matrix row/column reordering, nor animation controls. While reasonable for the purpose of this paper, their absence was noticed by several participants, and made their experience with the study more difficult. This suggests that such features should be carefully considered when designing future more extensive and elaborate studies.

The tasks are about the temporal nature of the graphs and are constructed for low level entities, such as individual nodes and links. We conjecture that the results may vary for much larger graphs exhibiting different structural properties or focusing on higher level entities, such as groups, clusters, and cliques. We also decide to focus on a fixed amount of time steps (each graph has four). For graphs with a large amount of time slices more interactive approaches would be better suited [18].

5 Conclusion

In this paper we presented an exploratory user study for different temporal encodings, JP, SI, and AN, applied to NL and M graph representations. We aimed at investigating, for each combination of representation and encoding, the user experience through a series of typical temporal graph tasks. We recorded the participants' response times, accuracy, and personal feedback. From the results, we observed that: (i) M had generally lower error rates and faster response times than NL; (ii) in JP, the participants disliked that they had to split their attention across multiple time slices; (iii) M with SI appears to be a promising research direction for the visualization of temporal graphs, considering its performance in terms of accuracy and response times in our study, and the impressions coming from the participants' feedback. The natural evolution of this work would be to generate a set of hypotheses, based on our results, to be tested on a more exhaustive user evaluation. This would be a forward step in providing a set of more precise guidelines and aesthetic criteria for the design of visualizations for dynamic graphs.

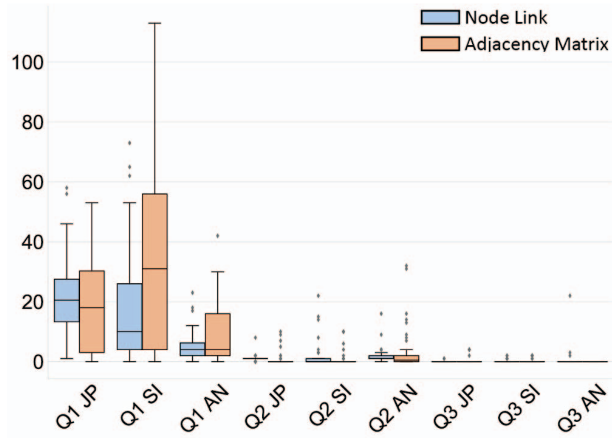


Figure 2: The absolute difference between the participants' answers and the correct answers for both NL and M representations, across all tasks and different temporal encodings (JP, SI, AN).

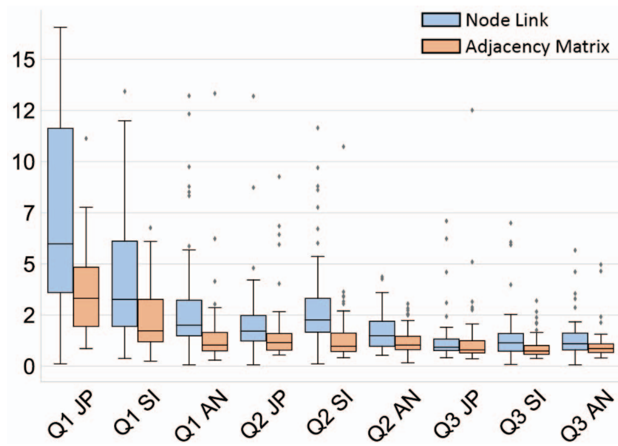


Figure 3: The response times (in minutes) of the participants for both NL and M representations, across all tasks and different temporal encodings (JP, SI, AN).

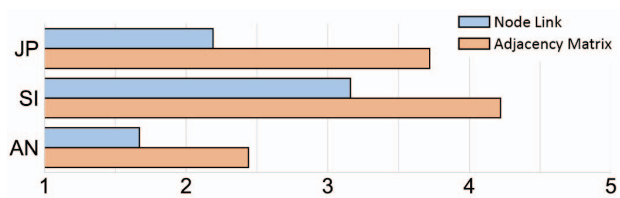


Figure 4: The average of the participants' preferences for each combination of graph representation and temporal encoding using a five point Likert scale (1 - least preferred and 5 - most preferred).

Acknowledgments

This work was conducted within the framework of the project KnoVA - Knowledge–Assisted Visual Analytics (P31419-N31) funded by the Austrian Science Fund (FWF) and partially supported by the "Smart Communications and Technologies" research cluster at TU Wien.

References

[1] J.-w. Ahn, C. Plaisant, and B. Shneiderman. A task taxonomy for network evolution analysis. *IEEE Trans. on Visualization and Computer Graphics*, 20(3):365–376, 2014. doi: 10.1109/TVCG.2013.238

[2] R. Albert and A.-L. Barabási. Statistical mechanics of complex networks. *Reviews of modern physics*, 74(1):47, 2002.

[3] D. Archambault, H. Purchase, and B. Pinaud. Animation, small multiples, and the effect of mental map preservation in dynamic graphs. *IEEE Trans. on Visualization and Computer Graphics*, 2011. doi: 10.1109/TVCG.2010.78

[4] D. Archambault and H. C. Purchase. Mental map preservation helps user orientation in dynamic graphs. In *Graph Drawing & Network Visualization*, pp. 475–486. Springer, 2013. doi: 10.1007/978-3-642-36763-2_42

[5] D. Archambault and H. C. Purchase. Can animation support the visualisation of dynamic graphs? *Information Sciences*, p. 495–509, 2016. doi: 10.1016/j.ins.2015.04.017

[6] F. Beck, M. Burch, S. Diehl, and D. Weiskopf. A taxonomy and survey of dynamic graph visualization. *Computer Graphics Forum*, 36(1):133–159, 2017. doi: 10.1111/cgf.12791

[7] C. Bennett, J. Ryall, L. Spalteholz, and A. Gooch. The aesthetics of graph visualization. In *Proc. of the Eurographics Conference on Computational Aesthetics in Graphics, Visualization and Imaging*, p. 57–64. The Eurographics Association, 2007.

[8] M. Bostock, V. Ogievetsky, and J. Heer. D3 data-driven documents. *IEEE Trans. on Visualization and Computer Graphics*, 17(12):2301–2309, 2011. doi: 10.1109/TVCG.2011.185

[9] I. Boyandin, E. Bertini, and D. Lalanne. A qualitative study on the exploration of temporal changes in flow maps with animation and small-multiples. *Computer Graphics Forum*, 31(3pt2):1005–1014, 2012. doi: 10.1111/j.1467-8659.2012.03093.x

[10] S. Diehl and A. C. Telea. *Multivariate Networks in Software Engineering*, pp. 13–36. Springer International Publishing, 2014. doi: 10.1007/978-3-319-06793-3_2

[11] M. Farrugia, N. Hurley, and A. Quigley. Exploring temporal ego networks using small multiples and tree-ring layouts. In *Proc. of the International Conference on Advances in Computer-Human Interactions*, 2011.

[12] M. Farrugia and A. J. Quigley. Effective temporal graph layout: A comparative study of animation versus static display methods. *Information Visualization*, 10:47–64, 2011.

[13] S. Ghani, N. Elmqvist, and J. S. Yi. Perception of Animated Node-Link Diagrams for Dynamic Graphs. *Computer Graphics Forum*, 2012. doi: 10.1111/j.1467-8659.2012.03113.x

[14] M. Ghoniem, J. . Fekete, and P. Castagliola. A comparison of the readability of graphs using node-link and matrix-based representations. In *IEEE Sym. on Information Visualization*, pp. 17–24, 2004.

[15] A. Hagberg, P. Swart, and D. S Chult. Exploring network structure, dynamics, and function using networkx. Technical report, Los Alamos National Lab.(LANL), Los Alamos, NM (United States), 2008.

[16] R. Keller, C. M. Eckert, and P. J. Clarkson. Matrices or node-link diagrams: Which visual representation is better for visualising connectivity models? *Information Visualization*, 5(1):62–76, 2006. doi: 10.1057/palgrave.ivs.9500116

[17] N. Kerracher, J. Kennedy, K. Chalmers, and M. Graham. Visual Techniques to Support Exploratory Analysis of Temporal Graph Data. In E. Bertini, J. Kennedy, and E. Puppo, eds., *EuroVis - Short Papers*. The Eurographics Association, 2015. doi: 10.2312/eurovisshort.20151133

[18] A. Lee, D. Archambault, and M. A. Nacenta. The effectiveness of interactive visualization techniques for time navigation of dynamic graphs on large displays. *IEEE Trans. on Visualization and Computer Graphics*, 27(2):528–538, 2021. doi: 10.1109/TVCG.2020.3030446

[19] R. Likert. A technique for the measurement of attitudes. *Archives of psychology*, 1932.

[20] S. Miksch and W. Aigner. A matter of time: Applying a data–users–tasks design triangle to visual analytics of time-oriented data. *Computers & Graphics*, 38:286 – 290, 2014.

[21] J. Moody, D. McFarland, and S. Bender-deMoll. Dynamic Network Visualization. *American Journal of Sociology*, 110(4):1206–1241, 2005. doi: 10.1086/421509

[22] M. Okoe, R. Jianu, and S. Kobourov. Revisited experimental comparison of node-link and matrix representations. In F. Frati and K.-L. Ma, eds., *Graph Drawing & Network Visualization*, pp. 287–302. Springer International Publishing, 2018.

[23] M. Okoe, R. Jianu, and S. Kobourov. Node-link or adjacency matrices: Old question, new insights. *IEEE Trans. on Visualization and Computer Graphics*, 25(10):2940–2952, 2019.

[24] H. Purchase, D. Carrington, and J.-A. Allder. Empirical evaluation of aesthetics-based graph layout. *Empirical Software Engineering*, 7, 2002. doi: 10.1023/A:1016344215610

[25] H. C. Purchase. The effects of graph layout. In *Proc. of the Australasian Conference on Computer Human Interaction*, p. 80. IEEE Computer Society, 1998.

[26] Purvi Saraiya, P. Lee, and C. North. Visualization of graphs with associated timeseries data. In *IEEE Sym. on Information Visualization*, pp. 225–232, 2005. doi: 10.1109/INFVIS.2005.1532151

[27] D. Ren, L. R. Marusich, J. O'Donovan, J. Z. Bakdash, J. A. Schaffer, D. N. Cassenti, S. E. Kase, H. E. Roy, W.-y. S. Lin, and T. Höllerer. Understanding node-link and matrix visualizations of networks: A large-scale online experiment. *Network Science*, 7(2):242–264, 2019. doi: 10.1017/nws.2019.6

[28] E. Stattner and N. Vidot. Social network analysis in epidemiology: Current trends and perspectives. In *5th International Conference on Research Challenges In Information Science*, pp. 1–11. IEEE, 2011. doi: 10.1109/RCIS.2011.6006866

[29] A. Vogogias, D. Archambault, B. Bach, and J. Kennedy. Visual encodings for networks with multiple edge types. In *Proc. of the International Conference on Advanced Visual Interfaces*. Association for Computing Machinery, 2020. doi: 10.1145/3399715.3399827

[30] V. Yoghourdjian, D. Archambault, S. Diehl, T. Dwyer, K. Klein, H. C. Purchase, and H.-Y. Wu. Exploring the limits of complexity: A survey of empirical studies on graph visualisation. *Visual Informatics*, 2(4):264 – 282, 2018. doi: 10.1016/j.visinf.2018.12.006