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NODKANT: Exploring Constructive Network Physicalization

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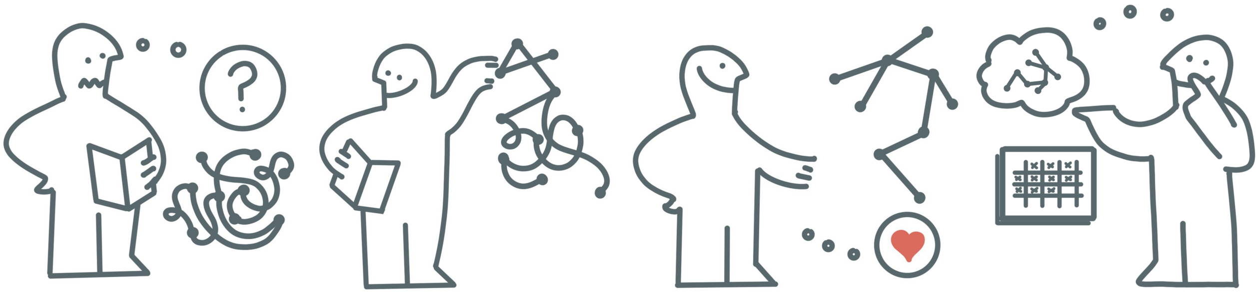

Figure 1: *The constructive network physicalization pipeline: A user is interested in analyzing relational data. Using instructions, and the* ***NODKANT*** *toolkit, they construct a node-link diagram, generating insights about the data on the fly. The user then analyzes the physical diagram, leveraging its versatility and engaging with it interactively. Insights generated during construction can be recalled after some time.*

Abstract

*Physicalizations, which combine perceptual and sensorimotor interactions, offer an immersive way to comprehend complex data visualizations by stimulating active construction and manipulation. This study investigates the impact of personal construction on the comprehension of physicalized networks. We propose a physicalization toolkit—**NODKANT**—for constructing modular node-link diagrams consisting of a magnetic surface, 3D printable and stackable node labels, and edges of adjustable length. In a mixed-methods between-subject lab study with 27 participants, three groups of people used **NODKANT** to complete a series of low-level analysis tasks in the context of an animal contact network. The first group was tasked with freely constructing their network using a sorted edge list, the second group received step-by-step instructions to create a predefined layout, and the third group received a pre-constructed representation. While free construction proved on average more time-consuming, we show that users extract more insights from the data during construction and interact with their representation more frequently, compared to those presented with step-by-step instructions. Interestingly, the increased time demand cannot be measured in users' subjective task load. Finally, our findings indicate that participants who constructed their own representations were able to recall more detailed insights after a period of 10–14 days compared to those who were given a pre-constructed network physicalization. All materials, data, code for generating instructions, and 3D printable meshes are available on* `https://osf.io/tk3g5/`.

CCS Concepts

• ***Human-centered computing*** → ***Visualization application domains; Empirical studies in visualization;***

1. Introduction

Network data comprise structured information that captures (complex) relationships, connections, and interactions between entities. Such data are encountered across various fields [RA16], including social sciences, biology, and computer science [LPP*06, JPS14]. Several representations—ranging from traditional node-link diagrams to adjacency matrices, and to hybrid or alternative approaches—have been proposed for visualizing network data [FAM23]. However, many individuals struggle to interpret the physical meaning behind these representations, potentially due to limited familiarity with network visualization [bor16, ASSB*23, GTS10]. Unlike other visualization techniques, such as a bar chart or a scatterplot, network visualization requires the interpretation of complex underlying data relationships. This suggests that both local characteristics (i.e., connectivity, attributes, etc.) and global topological patterns (i.e., network density, hierarchical structures, clusters, etc.) need to be easily distinguishable. Recent research underscores that core concepts in network visualizations remain challenging for many, limiting their ability to derive meaningful insights [SCP*16, ASSB*23]. Overcoming these challenges requires new methods that promote a deeper engagement with the data.

Data physicalization refers to the process of transforming abstract data into tangible forms, allowing users to *interact* and *engage* with them physically [JDI*15]. Compared to traditional screen-based methods, this approach makes complex data more accessible by stimulating perceptual and sensorimotor skills—fostering a deeper understanding and active engagement with the data. Conversely, constructive visualization (i.e., the construction of visualizations from physical tokens) encourages users to *build* data representations and stimulates deeper *reflection* on data compared to traditional tools [HCT*14]. This approach enhances learning and comprehension [Dea81] and also facilitates hands-on, personalized data representation [WBH24]. Similar principles are leveraged in products like IKEA® furniture or LEGO® [Gau14], where self-assembly creates a sense of accomplishment and enjoyment, experiencing the so-called "IKEA effect" [MNA12]. Combining data physicalization with constructivist principles offers an opportunity for network visualization to support users in building a mental map, while also enhancing their understanding of complex data relationships through physical engagement.

The combined potential of data physicalization [JDI*15] and constructive visualization [HCT*14, HJC14] has not been explored in the context of network visualization—particularly in terms of guiding users during the construction process. Specifically, whether users construct their networks freely or follow visual instructions, may significantly impact their efficiency, accuracy, and overall engagement with the data. To explore these factors, we developed a constructive network physicalization toolkit, **NODKANT** (see Figure 1), which enables users to build their own network representations (specifically, node-link diagrams) with physical tokens. **NODKANT** is a playful reference to IKEA's product naming tradition, blending "nodes" and "links" to embody our constructivist network physicalization toolkit. We, then, investigate how the way data is presented influences users' construction and interaction processes, comprehension, and memorability throughout and after the construction process in a mixed-methods lab study. Our *contributions* comprise:

- **NODKANT**: A network construction kit consisting of a magnetic surface, 3D printable physical tokens for the nodes, and edges of adjustable length. This allows the construction of node-link diagrams with spools, representing nodes, and threads between them, representing the edges of the network (see Section 3).
- A mixed-methods lab study to assess the users' construction process, comprehension, interaction mechanisms, and memorability throughout and after construction using our kit (see Section 4).
- Our findings on the benefits and challenges of constructive network physicalization (see Section 5), supplemented by a discussion on implications for network physicalization (see Section 6).
- Open resources: All materials, data, code for generating instructions, and 3D printable meshes are available on osf.io.

2. Related Work

In this section, we discuss network visualization and physicalization, as well as constructivist visualization. We, then, identify the research gap that we aim to bridge with **NODKANT**.

Network Visualization and Physicalization Approaches. Network visualization aims to create meaningful and intuitive representations to support gaining insights, understanding connections, and detecting patterns in network data. Sayama et al. [SCP*16] collaborated with researchers and educators to identify the essential network concepts for high school graduates. Börner et al. [bor16] studied 273 science museum visitors and found that while most people are comfortable with basic charts, they struggle with understanding network structures, such as topology and clusters. These challenges extend beyond novices, with AlKadi et al. [ASSB*23] showing that even analysts struggle to define exploration goals, identify relevant structures, and create appropriate visual mappings.

As reported by Yoghourdjian et al. [YAD*18], the visual complexity of graph visualizations is further influenced by several factors (i.e., size, density, etc.), increasing the perceptual workload of the intended users. A recent meta-survey [FAM23] underscores the breadth of the field of network visualization and highlights diverse challenges associated with the visualization of dynamic, complex, multivariate, and geospatial network data. Recently, Shu et al. [SPT*24] developed interaction supporting network learners to explain visual patterns and link them to data patterns.

Network physicalization has also shown promise for engagement and data comprehension in different domains, such as biology [DMB18], social science [Hem13], and art [MGD*24]. Drogemuller et al. [DCW*21] investigated the effect of network physicalization on comprehension, finding that 2D visual-haptic representations improved accuracy. McGuffin [MSF23] observed that interacting with augmented physical network layouts facilitated unique user interactions. Bae et al. [BFY*24] built upon this to develop a pipeline for network physicalizations that integrates sensing elements through electrical circuits, enabling interactive selections on physical networks. These efforts pave the way for exploring how constructivist approaches can complement and extend existing techniques by involving people deeply in the creation and exploration of network representations. Note that all the above studies heavily rely on the precalculation of 2D or 3D force-based layouts, which prohibits users from performing layout manipulations as an interaction scheme. Oppositely, **NODKANT** experiments with the levels of layout flexibility during the construction process.

Constructivist Visualization. In the field of constructive visualization, research has focused on democratizing the creation of visualizations, allowing non-experts to engage directly with datasets. Huron et al. [HCT*14] introduced a paradigm for users to create dynamic visualizations using wooden physical building blocks. They further demonstrate that constructive visualization enables novices to create visualizations [HCT*14] and spend more time on data-related tasks than using Excel [Kir10]. Recent work has developed several physical construction toolkits, such as Physikit [HGG*16], DataChest [WBH24], and SensorBricks [BVKVH24], which all use tangible elements, i.e., 3D printed tokens to create and explore data visualizations.

Studies have demonstrated the pedagogical potential of constructive visualization in both workshops and educational settings [HCBF16, KSB*23, WH16, Pun02, NP16]. These findings align with constructivist learning theory, where learners benefit from a "hands-on" approach through direct interaction with tangible objects rather than abstract methods [HJC14, VMP10]—a concept known as *discovery learning* [Dea81]. In LEGO® Serious Play [GV16], this concept is referred to as "thinking with your hands". Grounded in constructivist theory, it presents a method to facilitate problem-solving and communication, while creating an open system with infinite possibilities through creative play. The building is quick and straightforward and can be easily constructed, deconstructed, reviewed, and changed [Gau14].

Identified Research Gap. While prior work has explored physical and digital constructive approaches for traditional data representations (e.g., line charts, bar charts), there is a clear gap in utilizing these approaches to comprehend the relationships and the patterns of underlying network data. Studies on how user-generated graph layouts differ from automatically generated ones in the virtual space exist [vHR08, DLF*09]. Yet there are unique considerations for constructive approaches to the physical space. Thus, we investigate how different construction approaches can engage people to overcome these challenges. We investigate the impact of constructive approaches on network comprehension, building on network physicalization research [DCW*21, MSF23, BFY*24] and insights from constructive visualization [BZP*19, HCT*14].

3. Nodkant: A Network Physicalization Toolkit

We now set out to design a toolkit for network data physicalization. To begin with, we define a set of design requirements for such a network physicalization toolkit. Huron et al. [HCT*14] suggest that constructive visualization can profit from three creation paradigms: **simplicity, effectiveness, and dynamism**. We contextualize these paradigms in the scope of network visualization and our designs.

[Simplicity] ***Minimal number of parts and maximum amount of personalization.*** Using a simple case, Huron et al. [HJC14] demonstrate the versatility of square, colored, wooden tokens to create a multitude of different data representations. We follow this concept by minimizing the amount of unique parts in the representation, while simultaneously providing users with as much freedom in creating their personalized representations as possible. We argue that simple elements, when thoughtfully designed, can serve as versatile building blocks for complex systems. At the same time, they streamline the design, reduce cognitive load, and facilitate use.

[Effectiveness] ***Familiar and accurate representation of the concept.*** Networks have long been used by humans to represent entity relationships [MFD20], with node-link diagrams being arguably the most common representation [Tam16]. Applications like social network visualization [DLM24], transport networks [WNT*20], and biological networks [EBK*24] are intuitively understood methods to abstract complex phenomena.

[Dynamism] ***Make use of the physical nature of the representation.*** Data physicalizations possess unique abilities to engage audiences purely through their tangible nature [ZM08, WSK*19]. Digital representations commonly provide benefits such as interactivity, however, haptic interactions have also been explored and show benefits for physical network representations [DCW*21]. Recent developments, such as Bae et al.'s [BFY*24] computational pipeline to incorporate sensing into data physicalizations, represent a step towards leveraging the potential of interactivity in data physicalizations as well [PEW*24].

Designing NODKANT. Graphs that use edges represented as lines can benefit from improved readability [ANMMG24]. Straight-line node-link diagrams represent only one way to visualize network data [Tam16] and comprise two fundamental parts—*nodes* and *links*. In these diagrams, nodes represent entities or objects, while edges represent their relationships or connections, visually forming a network. These **simple** components can be used to easily create diverse network representations.

With **NODKANT**, we intend to provide an **effective** strategy to represent networks—akin to the way they are represented in literature and practical applications. Bae et al. [BFY*24] use spheres to represent nodes in their 3*D* network physicalizations. Their pipeline focuses on the sensing capabilities of their model and does label nodes to make them identifiable. Conversely, McGuffin et al. [MSF23] emboss the node labels into cuboids to represent nodes in their 3*D* network models. Drogemuller et al. [DCW*21] use spheres to represent nodes. Due to the limited size of their model, they also omit placing node labels. In **NODKANT**, a node is embodied by a spool, i.e., a flat cylinder as shown in Figure 2a. This shape can be easily produced using digital fabrication tools like a 3*D* printer or laser cutter. The top of the cylinder accommodates space for a node label, which can be simply written, attached as a sticker, printed, or laser-engraved.

Finally, we support the **dynamic** creation of our network physicalizations. When using fabrication to create network physicalization, creating nodes and edges in a single step limits the materials that can be used. The existing network physicalization methods [BFY*24, MSF23, DCW*21] create solid edges between the nodes. While this consolidates the network's structure, it limits the size of the representation due to the print surface and constrains the corresponding interactivity. To support the step-by-step creation of physical networks, we propose to use yarn to represent edges (Figure 2a). Using digital fabrication tools, we create a spool attached to each end of a length of yarn. This enables users to easily manipulate edge lengths if needed (Figure 2b). Placing a magnet underneath the spool creates a rotational axis for the spool at the contact point, which allows the edge lengths to be adjusted after the spool is placed. We design the spools to stack on top of each other, allowing a single node to have multiple connections (Figure 2c). The magnets provide enough stability to stay connected while the resulting stacks can be easily moved around on the surface. Note also that, based on this setting, a user can loosen the yarn to form various edge styles other than straight lines depending on their preferences.

4. Studying Constructive Network Physicalization

We assess our proposed **NODKANT** toolkit in an exploratory study evaluating the influence of personal construction on a user's comprehension of network data. The theory of *embodied cognition* in cognitive psychology proposes that human perception is strongly

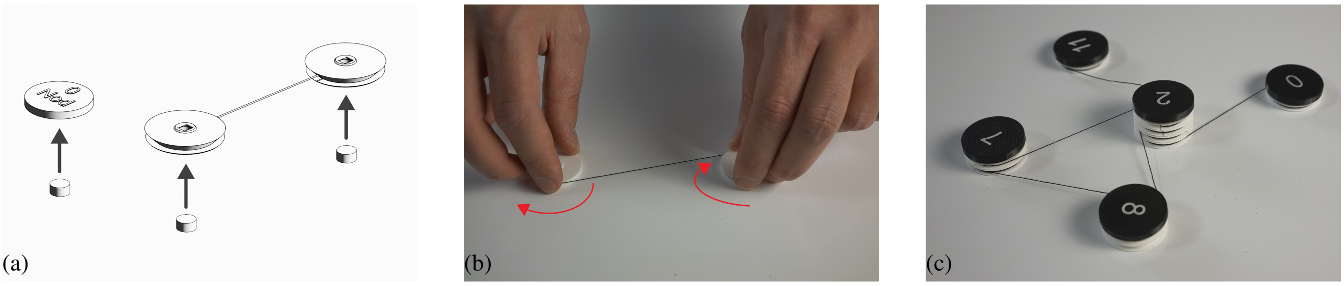

Figure 2: *Steps to create a **NODKANT** diagram. (a) Nodes are 3D printed and magnets are placed underneath, while edges are fitted with a length of yarn. (b) Edge lengths are adjusted by turning the spools until the edge has the desired length. (c) Edge spools and nodes are stacked vertically on a magnetic surface, where the magnets ensure stability until, step by step, a physical network is formed.*

connected to our interactions with the environment and how this influences learning processes [NEFM99]. Suwa and Tversky [ST02] show that creating representations of concepts, such as sketches, facilitates idea generation. Huron et al. [HJC14] investigate this further by employing generic physical tokens with which users freely create personalized data representations. Inspired by these approaches, our approach constitutes a physical method to create external representations for an abstract concept. While we restrict the visual representation to node-link diagrams, users retain the flexibility to determine the *layout*, which is an important part of the presentation mapping (geometry) [MGWP23].

4.1. Research Questions

The potential benefits of constructing a personalized physicalization, combined with the unique challenges inherent to network visualization present an interesting opportunity. We design our exploratory study based on four distinct research questions:

[RQ1: Construction] *What is the influence of different ways to present the data on user experience, while **constructing** the networks?* Constructive visualization enables a user to create a personalized representation of a given dataset. Limiting the representation to a node-link diagram still leaves plenty of room for customization. We investigate the impact of different methods to support a user during construction [WHJ23], on the user's experience.

[RQ2: Comprehension] *How does constructing a network physicalization impact a user's **comprehension**?* When users construct a personalized node-link diagram, they embody part of the presentation mapping in the visualization pipeline [JD13]. This process enables user interaction—even before the physical representation is fully realized [HJC14]. Conversely, user-created layouts may hinder readability compared to algorithmically optimized designs. To investigate this, we measure users' insight generation and performance in network analysis tasks, depending on *whether* and *how* they constructed their physicalization.

[RQ3: Interaction] *Which **interaction** patterns emerge from the use of **NODKANT**?* With **NODKANT**, we propose a network physicalization toolkit that supports the creation of node-link diagrams. Physicalizations inherently afford physical interactions through their physical embodiment [JDF13]. In our case, we see opportunities for interaction both *during* and *after* the construction process. To investigate this, we monitor users' interactions and analyze behavioral differences based on their construction method.

[RQ4: Memorability] *Does constructing a network physicalization impact **memorability**?* Physicalizations are more memorable than screen-based visualizations [SSB15, HMC*20]. To investigate *why* data physicalization supports users in remembering data, we measure delayed insight generation and task performance in a follow-up study.

4.2. Metrics

Quantitative Metrics. During the construction session, we measure the **time** taken by the participants during construction. To assess their subjective experience, we use the **NASA-TLX** questionnaire [HS88] as a benchmark. Additionally, we measure users' **time** and **accuracy** in completing benchmark tasks. For efficiency, we omit task-specific NASA-TLX evaluations and instead collect a single **subjective difficulty rating** from participants.

In the follow-up study, we ask participants **closed questions** about global properties like the represented entities and study context. We ask participants to recall known numeric properties and derive properties they did not calculate before. Finally, we include a Likert scale rating section into the follow-up to gather participants' subjective assessments of **NODKANT** by using four questions that relate to the **value** of visualization according to Stasko [Sta14] ("*The presented visualization was... i) trustworthy, ii) understandable, iii) available, and iv) quickly accessible*") and five questions that refer to the **emotional value** of visualization ("*The presented engaged in a... i) creative, ii) affective, iii) intellectual, iv) social, v) physical way*"), as defined by Wang et al. [WSK*19].

Qualitative Metrics. We **record** the construction sessions with an overhead camera setup and think-aloud protocol to analyze construction strategies, as well as interactions and thoughts during benchmark tasks. After construction, as well as the individual benchmark tasks, we ask participants to summarize their thoughts during construction and transcribe this as **open feedback**. Before the benchmark tasks, we record the open exploration of the network by the participants for an **insight**-based evaluation. In the follow-up study, we ask **open questions** about global and local structures and analyze the answers for insights.

4.3. Conditions

Our toolkit enables users to create personalized embeddings of network data, as we assume that the way **the dataset is presented** to the user may have a significant impact on their comprehension. Existing studies on user-created layouts in digital environments [vHR08, DLF*09] confronted users with unstructured layouts to rearrange. We opt instead to have our participants create a layout from scratch, better highlighting our toolkits' versatility. Wei et al. [WHJ23] present different strategies to guide users in creating personalized visualizations: *next-step*, *ghost*, and *gallery*. For our use case, we present a fixed visual mapping, the node-link diagram; thus, we will not investigate the gallery-based option, where users are shown representation alternatives to choose from. We base our conditions on these techniques.

Free Construction (FC). In *next-step*, a user is shown possible positions for the next step to take. In our case, this can be easily translated into a step-by-step placement of edges (Figure 3, FC). Edge lists represent network data by listing each connection between two nodes. When working with a randomized edge list, users can reconstruct the network by placing edges one at a time. However, this process often requires extensive rearrangement due to the randomness. We, therefore, opt to present the data to the user as a **sorted edge list**. Different sorting criteria are possible for this [Mey79], and to choose the most suitable one for our case, we compared sorting edges by *degree* of associated nodes, and following a *spanning tree* in a pilot study (see Section 4.4).

Layout Construction (LC). *Ghost* shows an outline of the final representation to the user, to indicate where tokens should be placed. The spatial embedding of a network is an area of ongoing research. To assist users in this process, we propose to provide users with a **pre-computed layout** as a means of presentation (Figure 3, LC). A force-directed layout algorithm ensures that the resulting layout conforms to established aesthetic criteria [Tam16]. To prevent users from getting lost while constructing their network, we provide step-by-step instructions on how to recreate the given layout, similar to instructions found in LEGO® or IKEA® manuals. To maintain consistency across conditions, the steps are presented in the same order as the edge-list in the (FC) condition.

No Construction (NC). A **NODKANT** diagram is a data physicalization—regardless of how (and by whom) it is constructed (Figure 3, NC). In the NC condition, we provide a group of participants with a **pre-constructed representation** of the layout, serving as a baseline for our comparisons.

Figure 3: *Study conditions.* **FC**: *Users freely construct their network from a sorted edge list.* **LC**: *Users construct a pre-computed layout using a step-by-step manual.* **NC**: *Users solve network analysis tasks using a pre-constructed layout.*

4.4. Pilot Study

As a first step, we conducted a small pilot study among six co-authors to determine which network size is suitable, i.e., the upper limit for a lab study. Additionally, as mentioned above, we compared two different sortings of the edge list for free construction scenarios to determine the most appropriate.

Procedure. We selected three networks (`grafo2693.13`, `grafo634.24`, and `grafo1034.29`) from Rome-Lib [BGL*97] based on node count, edge count, and density. Each participant assembled all three networks following a counter-balanced schema also alternating between FC and LC. For FC sessions, we tested two edge list sorting algorithms, one sorted by node degree and the other sorted along a spanning tree following node degree for non-spanning edges. We measured the time for each run and discussed emerging thoughts and implications.

Results. Completion times mainly depended on the edge number in the network, with the smallest network taking around 6–10 minutes, and the largest one taking 20–27 minutes to construct in FC. We noticed a broader variation of construction times in the FC condition compared to LC, owing to different strategies employed by the participants. In summary, we made the following decisions for the lab study based on our findings: Study times around 1 hour, we decided to use a dense **network with around 30 edges**. An edge list formed around a spanning tree leads to participants inefficiently using construction space sometimes, prompting us to favor the **sorting by node degree**. Dwyer et al. [DLF*09] suggest it may be intimidating to present users with a layouting task without usecase; therefore, we decided to **use data with relatable or recognizable context**.

4.5. Data

In our pilot study, we discussed the importance of a salient use case for our tasks. We decided to use the **animal contact network** from the network data repository [RA15], created for studying rabies propagation [RHGC15]. In the network, nodes represent raccoons and edges represent recorded contact interactions between them. In our pilot study, we identified that a network with approximate 30 edges should be feasible to construct within 30 minutes. Thus, we selected the `mammalia-raccoon-proximity-50` network with 16 **nodes and** 33 **edges** and assigned randomized names as labels to make it more relatable. The network density (0.1375) provides a sufficient challenge for analysis tasks [YAD*18], while the low number of nodes limits task complexity. Also, the origin of the data provides context for users to interpret the tasks.

4.6. Tasks

We select a set of tasks for our user performance evaluation from the network task taxonomy by Lee et al. [LPP*06]. Before exposing participants to benchmark tasks to measure completion times and error rates depending on the experiment condition, we ask them to freely examine the network. This allows us to transcribe the resulting statements and measure insight generation as proposed by North [Nor06]. We follow this with numeric observations about the **general overview**—namely counting or estimating the number of nodes and edges in the network. The remaining tasks are assigned according to a balanced scheme and we present them here in the order of occurrence in the taxonomy [LPP*06], orienting on *friend-of-a friend* scenarios. We select several topology-based tasks:

[Adjacency] *Find the most and least connected nodes in the dataset.* We use the context of popularity in a social structure and the corresponding risk of infection.
[Direct Accessibility] *Find out if three pairs of nodes are connected.* We employ the contexts of friendships and direct disease transmission.
[Indirect Accessibility] *Find all nodes accessible at a hop distance of two* for three different nodes. We employ the contexts of a *friend-of-a-friend* and the spread of infectious diseases.
[Common Connection] *Find the common neighbors* of three pairs of nodes. We employ the contexts of having common friends and infection by common contact.
[Connectivity] *Find bridge nodes in the network*, defined as nodes that upon removal cause a split of the network into components with at least two connected nodes. We use the contexts of connecting friend groups and isolating risk patients.
[Paths] *Find the shortest paths* between three pairs of nodes. We employ the contexts of connection in a social network and critical paths in contact tracing.

4.7. Recruiting

We recruited 27 university students, aged between 20 and 28 years for our study. Five of the students identified as female, the remaining 22 as male. Four of them had already completed a bachelor's program in computer science, and 23 had a high school diploma. All participants reported basic knowledge about networks, having completed a course on algorithms, where the concept is first presented. None of the participants had further education or professional experience with networks in a visualization context.

4.8. Procedure

We employed a between-subject design in our study. Participants were assigned to one of three groups, corresponding to one of the three conditions (**FC**, **LC**, **NC**) using a balanced scheme. All study participants received onboarding about node-link diagrams. We first explained to them the meaning behind the network, i.e., nodes representing individual animals, and the edges between them represent the interactions. We listed them two possible use cases for such networks: investigating i) social structures and ii) the corresponding ways of disease transmission. Every participant was instructed about the parts of **NODKANT** and was explicitly encouraged to interact with it freely during the tasks.

Construction. Participants from groups **FC** and **LC** received training on how to construct a network using **NODKANT**. They were given the option of free interaction with its components until they felt confident with them. After completing the scale ranking procedure of the NASA-TLX [HS88], participants were handed a printed set of instructions to construct the network: **FC** participants received a sorted edge list, while **LC** participants received an instruction booklet. After construction, we asked participants about their thoughts during the process. Conversely, participants in the **NC** group received a pre-constructed representation to observe instead of completing this step themselves.

Benchmark Tasks. With their physical networks in hand, we asked participants to reason about interesting global structures and interesting nodes they could detect. First, we asked them to count or estimate the number of nodes and edges. Then, participants completed a set of network exploration tasks. We provided a context for each task for the two use cases (social structures and disease transmission), explaining how the task may be relevant in a social network and disease-monitoring scenario. The order of tasks was counter-balanced across the participants using a Latin square scheme. We asked participants to think aloud during the tasks and leave feedback after each task. After all tasks were completed, we requested them to comment on at least one positive and one negative experience during their experiment and asked for additional informal feedback. Finally, we thanked the participants and concluded the on-site experiment.

Follow Up. Each participant received an online questionnaire exactly 10 days after completing the on-site study. Participants were first asked to recollect the context of the experiment and what nodes and edges were represented. We asked them to **freely recall** list interesting global and local structures in the network, without cues. Additionally, we provided them with **cued** questions on the number of nodes and edges, and edge density—a detail which they were not asked to calculate during the on-site part, to avoid receiving only memorized answers. Lastly, participants completed two Likert scale ratings about **NODKANT**. At the end of the questionnaire, participants were again thanked and received a debrief about the purpose and procedure of the study.

4.9. Analysis

Quantitative Analysis. Due to our between-subject study design, we obtain a sample of 9 participants per group, preventing meaningful statistical analysis. Thus, we omit statistical testing on the results and discuss the results purely visually. We compute the NASA-TLX [HS88] scores as weighted averages across the scales *Mental Demand, Physical Demand, Temporal Demand, Performance, Effort,* and *Frustration*, with weights as obtained in the scale ranking procedure. Task **accuracy** is computed as the ratio of correct observations to total observations in tasks with a set of nodes as answers, e.g. ground truth is (A,B), reported set is (A), accuracy is 50%. When the task is to determine a number, we report the accuracy as $1-|e_{rel}|$, where e_{rel} denotes the error relative to the ground truth, e.g. ground truth is 10, reported number is 9, $e_{rel} = 10\%$, and accuracy is 90%. For tasks that have three subtasks, we report the average accuracy across sub-tasks. We classify the **answers to the closed questions** in the follow-up as correct, semi-correct, and incorrect. For example, an answer to "*Which entity did the nodes represent?*" could be "*raccoon*" (correct, 100%), "*animals*" (semi-correct, 50%), or "*people*" (incorrect, 0%). We report the subjective **task difficulty** on a 1–10 scale (1-easy; 10-difficulty). Task and construction **times** are reported in m:ss. The time runs from when participants receive the assignment until they confirm to be satisfied with the result. In the case of subtasks, we report the total time for all tasks. In the subjective Likert scale ratings, we asked participants to rate their experience according to the scale *Disagree* → *Somewhat Disagree* → *Neutral* → *Somewhat Agree* → *Agree*.

Qualitative Analysis. We further **analyzed video** recordings and categorized the degree of interactions of our participants. We distinguish three categories: (1) the participant is *passive* or simply points at the representation, (2) the participant *touches* the network during the session without disturbing the layout, and (3) the participant *moves* the parts around.

We transcribed the participants' open feedback and further processed it, resulting in 521 individual utterances. We conducted two rounds of coding, one for categorization and one for rating insight-related utterances resulting from the first coding. Both were conducted by three independent coders (one was present in both procedures). For the **categorization**, we follow a combination of inductive and deductive coding [Chi97]. In the inductive session, each coder independently assigned a single concept to each utterance. Each coder produced their own set of codes, ranging between 21 and 105 different concepts. The coders then met in a joint session to produce a unified codebook resulting in 35 codes pertaining to 8 categories. After this, a deductive coding session took place, where the coders independently assigned these codes to the utterances. In another joint session, the coders discussed their assignments in cases where no consensus was reached. In a final individual session, each coder reviewed dissenting assignments. After that, the remaining 2-to-1 conflicts were resolved following a majority vote.

During the first coding procedure, we identified 149 comments from 5 different codes as **insights**. We categorize insights in three levels: (1) *reading data*, (2) *reading between data*, and (3) *reading beyond data* [SGA22]. The coders first assigned their rating. In a joint session, they discussed dissenting selections. In a second individual session, the coders revised their choices until no more conflicts remained that could not be broken by a majority vote.

5. Results

We present our results as they relate to each of our research questions (see Section 4.1), and summarize the implications of all relevant metrics (Table 1) to provide succinct answers.

5.1. RQ1: Construction

Quantitative Results. For **FC**, the median **construction time** was just under 27 minutes. The median for **LC** was about seven minutes faster. In the weighted average **TLX-score**, we observe a **higher median for FC** than for **LC** (**FC**: 33.67, **LC**: 22.67). We show the results for responses for the NASA-TLX across all sub-scales, as well as the weighted average in Figure 5. Notably, we observe a higher median in *physical demand* for **FC** (30) than for **LC** (20), as well as three very high ratings (≥ 80). We also observe higher medians in **FC** compared to **LC** for *performance* (**FC**: 40, **LC**: 15), effort (**FC**: 30, **LC**: 20) and *frustration* (**FC**: 25, **LC**: 10). Interestingly, *temporal demand* shows a very similar distribution for **FC** and **LC**, while we observe equal medians in *mental demand*, but a higher variation of ratings in **LC**.

Table 1: *Relation of metrics to research questions. ↑ placed after a condition indicates that the metric had positive implications for it, ↓ means negative. ↔ denotes ambiguous implications between conditions.*

		RQ1	RQ2	RQ3	RQ4
Quantitative	Construction Time	FC ↓			
	Construction TLX	FC ↓			
	Task Time		FC ↔ LC ↔ NC		
	Task Accuracy		FC ↔ LC ↔ NC		
	Task Difficulty		FC ↔ LC ↔ NC		
	Value (Traditional)		FC ↓		
	Value (Emotional)		FC ↔ LC ↔ NC		
	Follow-up Accuracy		NC ↓		NC ↓
Qualitative	Construction Strategy	FC ↑			
	Physical Properties	FC ↓ LC ↓		FC ↑ LC ↑	
	Interaction			FC ↑	
	Usability		FC ↓ LC ↓		
	Task Load		FC ↓ LC ↓		
	Engagement		FC ↑ LC ↑		
	Feedback	FC ↔ LC		FC ↔ LC	
	Insights		FC ↑		NC ↓
	Video			FC ↑	

Qualitative Results. We found a total of 28 (**FC**:20, **LC**:8) utterances referring to strategies during **construction**. Five **FC** participants *followed instructions* ("*worked from node to node in order they came up*") and used our edge list sorting, while four reported individual *sorting strategies* ("*looked at which names come up more often for the best start*"). Six **FC** participants started *forming clusters* during construction ("*noticed clusters forming so I kept them in separate areas*"). Five **FC** and three **LC** participants remarked on rearranging nodes during construction ("*Moved nodes around a lot during construction*", and "*should have checked [the] final outcome before, [and] had to rearrange a bit*", respectively). Only **LC** participants expressed strategies concerning *label placement* during construction. 10 comments on **task load** were related to strain during construction (**FC**:4, **LC**:6). In **FC**, two comments referred to *frustration*, one to increased *temporal effort*, and one to low *performance*. For **LC**, one comment referred to lowered while three to increased *mental demand*, and three comments referred to increased *temporal* and *physical effort*, each. Two comments represented **feedback** on possible *physical improvements* of spool handling. **Visual inspection** of construction results shows that **FC** led to more "messy" representations than **LC**.

Summary RQ1: Construction. Our findings indicate that constructing diagrams with **NODKANT** takes longer on average and has a slightly higher impact on a user's task load when using **FC** compared to **LC**. Interestingly, the **TLX scores do not show an impact of the longer construction times in FC**. **FC** results are less refined compared to the outcome of **LC** (see Figure 4-a,b). Many negative comments overall refer to frustration caused by difficulties with string tension. Yet, we find indications in the qualitative data that during construction **FC participants were deeply engaged** and worried more about global issues like emerging clusters, while **LC participants' major concern lay in the aesthetic details**, such as keeping the edges straight.

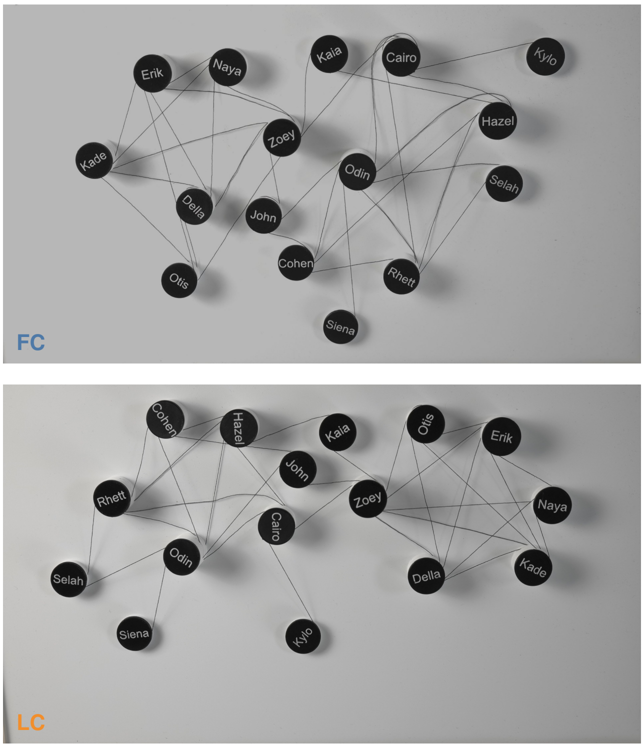

Figure 4: *Example layouts.* **FC** *graphs use a lot of space and edges are often loose.* **LC** *graphs closely resemble the given layout.* **NC** *participants were given a faithful recreation of the* **LC** *layout.*

5.2. RQ2: Comprehension

Quantitative Results. Overall, task **completion times** between all groups were similar, with **FC** ($avg = 01{:}52$) being on average 30 seconds slower than **LC** and **NC** (both $avg = 01{:}22$). Because three participants took particularly long, the average **time for the *connectivity* task in LC was about double compared to LC and NC** (**FC**: 02:55, **LC**: 01:24, **NC**: 01:15). We observe notably higher median completion times for **FC** in the tasks *common connections* (**FC**: 01:46, **LC**: 01:15, **NC**: 01:27), *indirect accessibility* (**FC**: 04:08, **LC**: 03:20, **NC**: 03:12) and *overview* (**FC**: 01:10, **LC**: 00:40, **NC**: 00:41). We also observe high **accuracy** for all conditions on average across all tasks. In the *overview* task, we observe a lower median accuracy for **FC** (**FC**: 78.79, **LC**: 90.91, **NC**: 90.91). Across all benchmark tasks, **LC** participants rated the tasks **difficulty** highest on average, followed by **FC**, and **NC** (**FC**: 3.82, **LC**: 4.16, **NC**: 3.13). Median ratings for **FC** were notably higher compared to the others for the *connectivity* task (**FC**: 7, **LC**: 4, **NC**: 4), while **LC** ratings were higher for *indirect accessibility* (**FC**: 4, **LC**: 6, **NC**: 4) and *overview* (**FC**: 4, **LC**: 5, **NC**: 4). The median rating for **LC** was lower than others for *paths* (**FC**: 4, **LC**: 4, **NC**: 3), while **FC** was rated lower for *adjacency* (**FC**: 1, **LC**: 2, **NC**: 2).

In terms of traditional visualization values [Sta14], the **NC** and **LC** participants gave high marks for *trust, understanding,* and *availability* of information. **FC** participants rated *timeliness* mildly negative. For the emotional values, we observe generally low affection, the least from the **NC** group. Here, **LC** participants rated *intellectual engagement* and *creativity* strongly positive, while *physical engagement* was ranked strongly positive by **FC** participants.

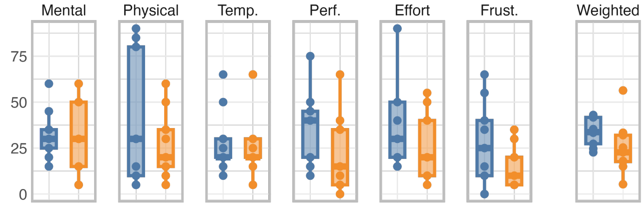

Figure 5: *NASA-TLX ratings for network construction.* **FC** *participants report higher physical demand, overall effort, and frustration, as well as less performance satisfaction than* **LC** *participants, yielding a slightly higher weighted average score for* **FC**.

Qualitative Results. Figure 6 shows a comparison of **insights** recorded on-site with insights recorded in the follow-up questionnaire. We classified a total of 274 comments as insights, out of which 149 were recorded on-site and 125 in the follow-up. On-site, we see that **FC** participants had most insights (**FC**: 57,**LC**: 45, **NC**: 47), and the most deep insights (**FC**: 17,**LC**: 13, **NC**: 6). **On-site**, **FC** participants most notably identified more insights on *adjacency* (“*Zoey and Odin seem to have a lot of friends*"), and *connectivity* (“*seems like Kaia and John are connections between the two groups*"). *Cluster-identification* (“*easily splits in two groups*"), *density* (“*one side is strongly connected*"), and *outlier* identification (“*some animals have only one contact*") were similarly represented in the collected insights across the groups, with **FC** participants reporting slightly fewer for each category. 59 comments were related to participants' **task load** during the benchmark tasks (**FC**:25, **LC**:21, **NC**:13). 35 comments refer to *mental effort*, while 24 of them point to a increase (**FC**:11, **LC**:11, **NC**:2) and 11 to alleviation (**FC**:5, **LC**:5, **NC**:1). Increased *physical effort* was only reported by **FC** and **LC** participants (**FC**: 4, **LC**: 1). Six comments refer to *frustration* (**FC**:5, **LC**:1). Overall, *effort* was mentioned 8 times—equally often in positive as in negative connotation (**FC**:2, **LC**:2, **NC**:4). Four participants remarked negatively on their performance (**FC**:3, **LC**:1). While five **FC** and **LC** participants reported increased temporal effort (**FC**:2, **LC**:3), five **NC** participants reported positive experiences in the context. 84 of our transcribed utterances refer to the general **usability** of **NODKANT**.

Layout clarity was the subject of 37 comments in total. Two utterances for each group refer to it positively (“*topology is quite clear*"). The 31 negative comments occurred predominantly among **FC** and **LC** participants (“*the messy structure made it a bit harder*") (**FC**:17, **LC**:11, **NC**:3). 17 utterances were classified as expressing participants' *uncertainty* (“*not sure if there was a single shortest path*"). Most of these originated from **LC** participants (**FC**:5, **LC**:11, **NC**:1). We coded 13 comments as referring to participants recalling details about the graph from *memory* (“*knew the answer from the general overview, just checked if it was right*") during the tasks (**FC**:5, **LC**:5, **NC**:3). Seven statements related the experience during the study to *learning* (“*it is very nice recap for graphs*") (**LC**:4, **NC**:3). *Intuitivity* in solving the tasks was predominantly reported by **NC** participants (**FC**:5, **LC**:5, **NC**:3). We received two comments

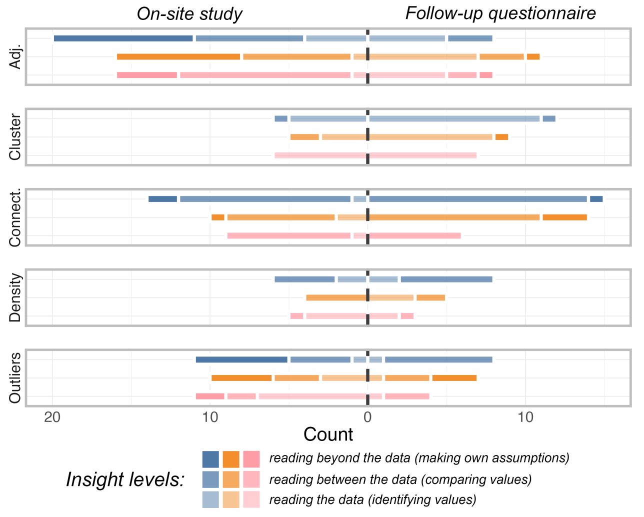

Figure 6: *Insight codes distribution per group. Center to left: On-site study insights, with FC participants reporting more insights than LC and NC. Center to right: Follow-up insights, where NC participants report notably fewer insights. Lightness indicates insight level.*

praising the clarity of our *instructions* by LC participants. A total of 34 comments refer to **engagement** (FC:15, LC:14, NC:5). Of the 14 *affectionate* statements("*playful experience, it was fun!*"), comparably few refer to NC (FC:6, LC:5, NC:3). Similarly, *intellectual engagement* was predominantly reported by FC and LC (FC:5, LC:5, NC:2). Finally, only FC and LC participants reported *physical engagement*. Six participants gave **feedback** in the form of *visual improvement* suggestions, such as coloring nodes and edges.

Summary RQ2: Comprehension. Bearing in mind the stark differences in visual appearance between the different representations, as shown in Figure 4, the results above are surprising. Firstly, the **impact of the construction method on task time and accuracy is negligible**. FC participants had to work with their—much messier—graphs, often impacting tasks that are supported by layout clarity, increasing mental effort, and uncertainty , ultimately lessening trust. However, **FC participants reported more and deeper insights** on the first inspection and were physically engaged by construction.

5.3. RQ3: Interaction

Analyzing our **recordings** of the on-site study reveals that NC participants never touched the graph and only performed *pointing* interactions. Comparing FC and LC recordings shows that FC participants had more *touch*-based contact (FC: 4, LC: 1) and *moved* parts around on the canvas more often (FC: 4, LC: 2). 63 comments related to **physical properties** of **NODKANT**, the least of which come from participants in the NC group (FC:26, LC:29, NC:8). The only physical property referenced by NC was the *height* of the spool stacks, which some participants recognized as an indicator for node degree ("*its nice because the node height indicates degree.*") (FC:12, LC:9, NC:8). FC and NC participants additionally reported problems with *string tangling* (FC:2, LC:2). *String tension* (FC:11, LC:14) and insufficient *string length* (FC:1, LC:4) most often caused problems during the LC condition. Our participants refer to **interaction** techniques to solve benchmark tasks on 86 separate occasions. Most of these comments refer to *visual techniques* ("*went clockwise from the starting node and ticked them off*"), most of which originate from NC participants (FC:8, LC:21, NC:44). Only FC and LC participants report using *physical techniques* to solve the benchmark tasks (FC:9, LC:4). We show the interaction techniques our participant used in Figure 7. Four participants moved nodes individually to determine connections to neighbors ("*I wiggled the nodes and checked if neighbors wiggle*," Figure 7 (a)). Three participants refer to manipulating edges ("*tugged on the strings to see the connections better*," Figure 7 (b)). Two reported manipulating two nodes at once ("*if you pull two edges apart and see the lines that get straight you can check if they connect to a common neighbor*," Figure 7 (c)). Two participants reported comparing node heights by rearranging the graph ("*counted like coins by pushing the stacks close to each other*," Figure 7 (d)).

Summary RQ3 : Interaction. Despite explicitly encouraging all participants to physically interact with the representations, we observe that **physical interaction after construction occurred only in FC and LC**. Additionally, despite constructing the representations, **LC participants rarely interacted physically with the graph**. Unsurprisingly, NC participants who did not construct a graph never physically interacted with it. We conclude that **free construction motivates people to physically engage with their representation** more.

5.4. RQ4: Memorability

Memorability was investigated in the follow-up study conducted online 10–14 days after the on-site part of the experiment.

Quantitative Results. Average accuracy for **closed questions** was 73.01%, with LC participants' accuracy being slightly lower than others (FC: 75.31, LC: 66.06, NC: 77.91). While most participants across all groups remembered what the *entities* in the graph represented, most NC participants answered only partially correctly on the question on the defined *relation*. Most participants at least remembered one of the given *contexts*. On average, LC participants had lower accuracy in remembering *node count* (FC: 89.58,

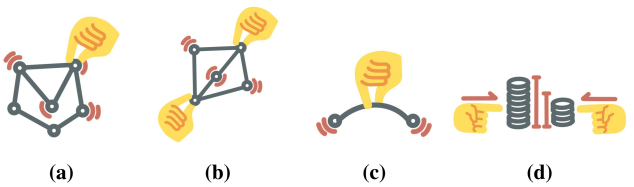

Figure 7: *Different interactions with* ***NODKANT****. (a) Wiggling a single node reveals connections. (b) Tugging on nodes reveals common neighbors. (c) Pulling an edge shows connected nodes. (d) Pushing nodes together allows direct comparison of degree.*

LC: 70.14, **NC**: 92.19) and *edge count* (**FC**: 65.82, **LC**: 44.11, **NC**: 77.78), while all three groups did comparably well in deriving the average node degree (**FC**: 84.72, **LC**: 83.33, **NC**: 86.11).

Qualitative Results. Most notably, **NC** participants reported the least **insights** (Figure 6) overall (**FC**: 51,**LC**: 46, **NC**: 28). In general, the insights recorded in the follow-up were classified lower on average, with **LC** participants remembering the most deep insights (**FC**: 1,**LC**: 7, **NC**: 1). **FC** participants retained more insights on *clusters*, *connectivity*, *density* and *outliers*, while **LC** participants recounted more insights on *adjacency*.

Summary RQ4: Memorability. Here, quantitative results show that most participants recalled questions that were asked in the on-site part and could even derive the average node degree relatively accurately, which was not asked before. This attests well to the general memorability of data physicalization. More interestingly, the distribution of reported insights in our follow-up indicates that **constructing a physicalization makes it more memorable**. While we acknowledge that time spent with the representation may be a confounding factor for this, we also observe deeper insights retained in **LC**, which points towards a **positive influence of readability on memorization**.

6. Discussion and Conclusion

Comparison with Related Work. Van Ham and Rogowitz [vHR08] found that users tend to enclose clusters in hulls when arranging graphs. We show that such patterns occur similarly in physical settings. In addition, our results show that a constructive approach supports the **generation of early and deep insights on the presented data**. We pose constructive approaches like **NODKANT** could support analytical reasoning (Figure 8a). Moreover, we show that our toolkit supports physical interaction with our representation and spatial perception of the embodied data. While it does not support the construction of "real" three-dimensional graphs like Bae et al.'s [BFY*24] or McGuffin et al.'s [MSF23] approaches, it uses its 2.5-dimensional properties to convey certain aspects of the graph intuitively. Moreover, as opposed to static contemporary approaches, such as the one presented by Drogemuller et al. [DCW*21], **our technique invites "analog" manipulation** that can be used to navigate network data. While Dwyer et al. [DLF*09] show various interaction patterns of users creating graph layouts on touch screens, **NODKANT** affords unique physical interaction even after construction. While they observed that user-generated layouts could influence performance, our participants were able to compensate for the messiness of their self-generated layouts through familiarity. In the past, physical data representations have been shown to be more memorable than virtual representations [SSB15, HMC*20]. Recently, Pahr et al. [PEW*24] demonstrated that interactivity can enhance the perception of an active physical representation. In contrast, we show that even **interaction during construction makes physicalization more effective and memorable**, presenting a unique opportunity for physical data representations. Future work in data physicalization could make use of constructive metaphors, allowing users to be more involved and creating useful insights into the presented data.

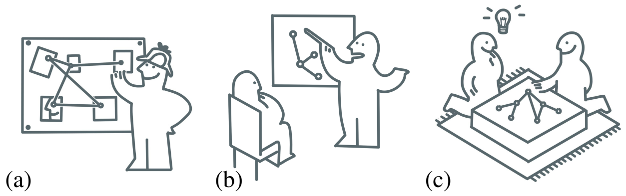

Figure 8: *Applications of constructive network physicalization.*

Limitations and Future Work. Our study participants were able to build a small network and completed a series of benchmark tasks with **NODKANT**. We acknowledge that participants often had problems keeping the edges straight, leading to tangling and confusion. While we show that the downsides of this are compensated by physical interactions and memorability, we acknowledge that **users need to be supported during the construction process**. For instance, designing self-retracting edge spools could mitigate the cognitive and physical overhead of construction and allow users to engage more with the data—as opposed to graph aesthetics. We also acknowledge that due to time constraints, only a single network dataset was investigated. As such, investigating how network size and density influence the interaction with **NODKANT** is left for future work. Also, our study population is comprised mainly of young, educated male students. This allowed us to rely on their experience in navigating data visualization. An interesting avenue for future work would be to investigate how the user's involvement while constructing a representation influences their visual literacy, for example in **educational** settings (Figure 8b).We also performed isolated experiments with one user at a time, thus limiting the **social aspect** of engagement [WSK*19]. The **NODKANT** toolkit itself does not rely on experience with visualization and only requires a few cheap and easily accessible parts. This could support workshops where groups of people **collaboratively** construct a representation of community-relevant data (Figure 8c).

Concluding Remarks. We provide users with a simple, effective, and dynamic toolkit for constructing network physicalization. Huron et al. [HJC14] propose that this allows a user to make use of the "visual mapping" stage of the visualization pipeline [JD13]. By limiting the toolkit to the construction of node-link diagrams, we allow users to engage in the "presentation–mapping" part of the pipeline. **NODKANT** demonstrates how physical interaction with data can enhance the sense-making process through construction.

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