New Materialist Network Approaches in Science Education: A Method to Construct Network Data from Video

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Abstract

Lately, new materialism has been proposed as a theoretical framework to better understand material-dialogic relationships in learning, and concurrently network analysis has emerged as a method in science education research. This paper explores how to include materiality in network analysis and reports the development of a method to construct network data from video. The approaches, 1) information flow, 2) material semantic and 3) material engagement, were identified based on the literature on network analysis and new materialism in science education. The method was applied and further improved with a video segment from an upper secondary school physics lesson. The example networks from the video segment show that network analysis is a potential research method within the materialist framework and that the method allows studies into the material and dialogic relationships that emerge when students are engaged in investigations in school.

Keywords: upper secondary school physics; project-based learning; video-based research

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1. Introduction

Science education research has been criticized for its tendency to ignore material culture and how it is theoretically centred in social culture and especially in discursive practices (Milne & Scantelebury, 2019; Hetherington et al., 2018). In recent years, new materialism has been seen as a potential theoretical approach to start answering this criticism.

Although there are different orientations of new materialism, it is quite widely agreed that the privileged role of humans is diminished and the role and meaning of materials is emphasised (Gamble et al., 2019). Current research engaging in new materialism has studied, for example, science teachers' thoughts about the role of materials (Hetherington & Wegerif, 2018) and the use of microblogging to support students' conceptual development (Cook, Warwick, Vrikki, Major, & Wegerif, 2019). There has also been theoretical work to understand better the role of materials in science learning by Hetherington et al. (2018), who propose a theoretical framework based on Barad's agential realism and a Bakhtinian dialogic pedagogy.

For science education, new materialism implies that, in addition to the students, materials such as laboratory equipment and instruments themselves play an active role in constructing knowledge. Moreover, knowledge is not independent of the context, such as the investigations and the material world in which it was constructed. This active role of materials has not been adequately theorised even though there has been research into how and why students should engage in investigative activities (Hetherington et al., 2018). Although different research orientations have included materiality to a varied degree, typically the instruments are seen as passive tools that when used correctly will produce the expected or correct values. The instruments are given higher authority than the students who use them, and thus the instruments are taken for granted (Milne, 2019). For example, project-based learning (PBL) in science sees instruments in conjunction with cognitive tools (Krajcik & Shin, 2014). The cognitive tools enable students to achieve learning goals that are otherwise unattainable. For example, using data loggers and computer-based laboratory tools, computers function as cognitive tools that show graphical representations of the data. These representations then allow students to see patterns in the data, providing insight into the phenomena students are investigating and enabling knowledge construction.

In the new materialist view, computers are seen as active participants in knowledge construction. A Computer can modify or even process information or data; for example, the raw data acquired by a sensor from the phenomena is processed and displayed in graphical form. Therefore, the computer offers information in a more comprehensible form to the students (actors) who are affected and can construct new knowledge of the phenomena. Thus, the computer has become non-human actor in knowledge construction. This kind of interconnected or networked nature of knowledge construction is a feature of new materialist theories, especially in the work of Bruno Latour (Latour & Woolgar, 1979; Latour, 2005). The Actor-Network Theory (ANT) aims to explain social by tracing associations of actor-networks that include human and non-human actors (Latour, 2005). In education, ANT has been used to understand curriculum or policy development (Fenwick & Edwards, 2017) and has also been employed in educational reform studies (Nespor, 2002; Fenwick, 2011).

We focus here on students' investigations and collaboration. Consequently, we use a different conceptualisation of a network than the actor-networks of ANT. Networks based on graph theory are used to analyse and visualise the collection of connected elements, such as communication or social systems (Barabási, 2012). In science education research, it has been proposed that these network-based approaches complement other research methods (Koponen & Mäntylä, 2020) and they have been used to study, for example, classroom interactions (e.g., Bokhove, 2018) and classroom discussions (e.g., Bruun, Lindahl, & Linder, 2019). In education, networks are applied mainly through Social Network Analysis (SNA). Although the two network approaches, SNA and ANT, differ in their theoretical background and applications, both could benefit from the ideas of the other (Vicsek et al., 2016). In particular, the SNA researcher should develop methods that include non-human actors in the networks alongside human actors.

In this article, we explore how to include materiality in network analysis and develop a method to construct network data from video within the new materialist perspective in order to understand better the role of material and dialogic relationships in science learning. Students' investigations provide a rich setting to develop a method applying sophisticated network analysis techniques. We begin with a brief review concerning the way in which networks have been used in science education research, and examine what possibilities there are to include materiality in different network approaches. Additionally, an authentic video sample from an upper secondary school physics lesson is used to develop new materialist network approaches.

2. Network Analysis in Science Education Research

A network is a collection of nodes (also called vertices or points) that have pairwise connections known as edges (also called links or arcs) that represent a real-world system. The nodes can represent, for example, computers, humans or cities, and the edges represent internet connections, social relationships or railway sections, respectively. Depending on what the network represents, the edges may be directional, showing the direction of the connections or edges can have weight to indicate the strength of the connection. Weighted directed networks are also possible. Examples of basic directed and weighted networks are shown in Figure 1.
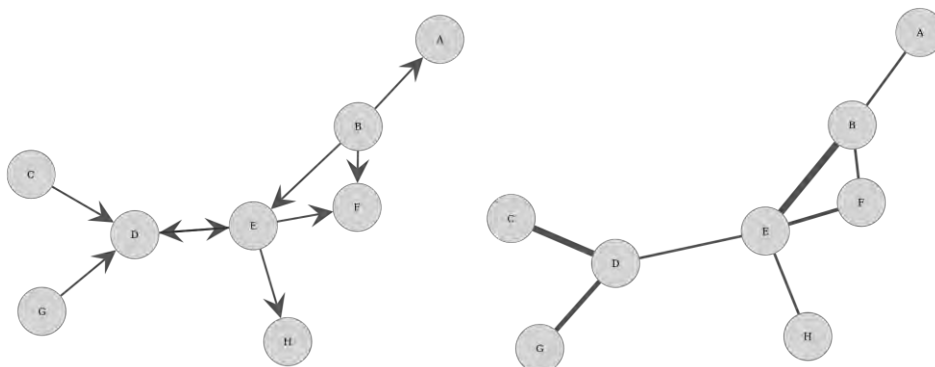

Figure 1. Examples of a directed simple network (left) and a weighted network (right).

The analysis of networks is based on local or global measures characterising the whole network or distinct nodes or edges. One common network measure in social sciences is the different centralities (Knoke & Yang, 2008), like the degree centrality, which refers to the number of edges a node has. For example, node E is the most central with a node degree of four in Figure 1. The more edges a node has, the more central and thus more relevant it is. Even though centrality measures are often used, networks can also be analysed using network motifs or roles. Network motifs are considered the building blocks of networks (Milo, Shen-Orr, Itzkovitz & Kashtan, 2002). For example, in Figure 1 nodes C, D and G form one triadic motif, and in the directed network the role for nodes C and G is the source, whereas D node's role is the sink.

Zweig (2016) argues that for a network analysis to be purposeful there should be flow within the network. This flow originates from local exchange of, for example, used goods, money or e-mails that are transferred or replicated between nodes. In different types of networks this flow is implied to be information; for example, computers connected with the internet or other communication networks. Similarly, social networks enable exchange of information between people. However, whereas e-mails

are often sent to multiple recipients, confidential gossip is told to one person at a time, and therefore the flow process is different in the respective networks. Understanding the flow process within the network is important in order to choose the right analysis methods, as different centrality measures are appropriate for different types of flow (Borgatti, 2005).

In education research, network analysis is often understood as the analysis of social networks. Social network analysis (SNA) is the study of social connections and structures using networks (Wasserman, 1994). In SNA the nodes represent people, and the edges represent social connections. These connections can be constructed from social media, questionnaires or otherwise reported relationships or interactions. For example, SNA has been used to study online written communications (e.g., Martínez, Dimitriadis, Rubia, Gómez, & De la Fuente, 2003; Turkkila & Lommi, 2020) and classroom interactions. These interactions have been defined differently, but usually they are connected to student discourse. The types of interactions include each individual utterance between actors (Bokhove, 2018), taking turns in argumentation (González-Howard, 2019), or discussion in joint work (Dou & Zwolak, 2019).

In addition to analysing social networks, science education research networks have also been used to analyse texts or the content of discussion. For example, Bruun et al. (2019) applied semantic networks to analyse annotated speech as text to characterise the whole content of the discussion. This approach adopts the same techniques used in the network analysis of textbooks (Yun & Park, 2018) and students' written answers (Wagner et al., 2020). Similar, but distinct from semantic networks, are conceptual networks that study subject-specific concepts found in texts or utterances (Caballero et al. 2020) or in concepts maps (Koponen & Nousiainen, 2019). There is also Epistemic Network Analysis (ENA), which considers epistemic elements coded from text or speech as nodes instead of single words or concepts (Shaffer at al., 2009). Co-occurrence of the epistemic elements are mapped temporally to investigate, for example, how students share and improve ideas (Oshima, Oshima & Saruwatari, 2020) and how student discourse supports the development of scientific practices (Bressler et al., 2019).

2.1 Including the material

New materialism sees humans as only one type of agent that never acts in isolation of each other (Bennett, 2010). In science classrooms or laboratories there are other non-human actors with whom humans act together. Thus, the network could comprise these human and non-human actors instead of solely humans. If a network of students can be characterised by the exchange of information, it would be possible to consider laboratory equipment and digital tools as actors capable of providing information (e.g., a graph on a computer screen) to the students. Similarly, the measuring apparatus provides students with qualitative information about the phenomenon they are studying (assuming that the phenomenon is visible). Thus, a network could be constructed where, for example, computers and other devices that are used to measure and observe phenomena would be nodes alongside students and there would be information exchange between these nodes that would constitute directed edges within the network.

If the students are engaged with materials during their discussions, these materials should appear within the student dialogue and therefore within a network constructed from annotated dialogue. However, how the materials appear within the annotations might not be straightforward, and combination with content analysis might be needed. An approach based on semantic networks rather than conceptual networks should be more applicable as the material references may or may not be connected to (physics) concepts. In any case, the network would consist of words relating to the topic of students' investigations, science concepts or materials as nodes and semantic connection between words are represented by edges. This kind of material semantic network could show how materials are semantically linked or embedded within student dialogues.

An additional approach is inspired by assemblages of the material-dialogic framework (see of Hetherington et al., 2018). These assemblages are continually formed, dissolved and re-formed by agents engaging materially and dialogically. Engaging with materials is seen as embodied actions, like

pointing or manipulating an object, and hence bringing the material directly into the dialogue. Similarly, students engage with each other verbally, and through these engagements spoken dialogue and materials are linked. Thus, it would be possible to construct a network from these material and verbal engagements, where engagements are represented by the edges in a network of agents.

In conclusion, we have identified three possibilities for new materialist network approaches: information flow, material-semantic and material engagement networks. In the next section we explore how these approaches can be applied with a video sample of students' investigations.

3. Constructing material network data from video

Typically, in video-based research, video file or recording itself is not considered as data but is instead a source of data. How to define that data is a key challenge in video analysis (Erickson, 2012). Our aim is to construct network data from video; the information used for this construction is student (and teacher) dialogue and their embodied action with each other and the materials evident within the video. We begin with an outline of the method to give general overviews of the process. Afterwards we provide a detailed account of the video selection and specific descriptions for each network approach.

3.1 Overview of the data processing

The flowchart in Figure 2 shows an outline of the process. After selecting a video segment for analysis, precise annotations of student and teacher talk are made. Next, descriptions of students' embodied actions are added in brackets next to the annotations. Similarly, students' referencing materials are described and added in brackets into the annotations. The steps up to this point are made within the annotation software when referencing back to the video is needed.
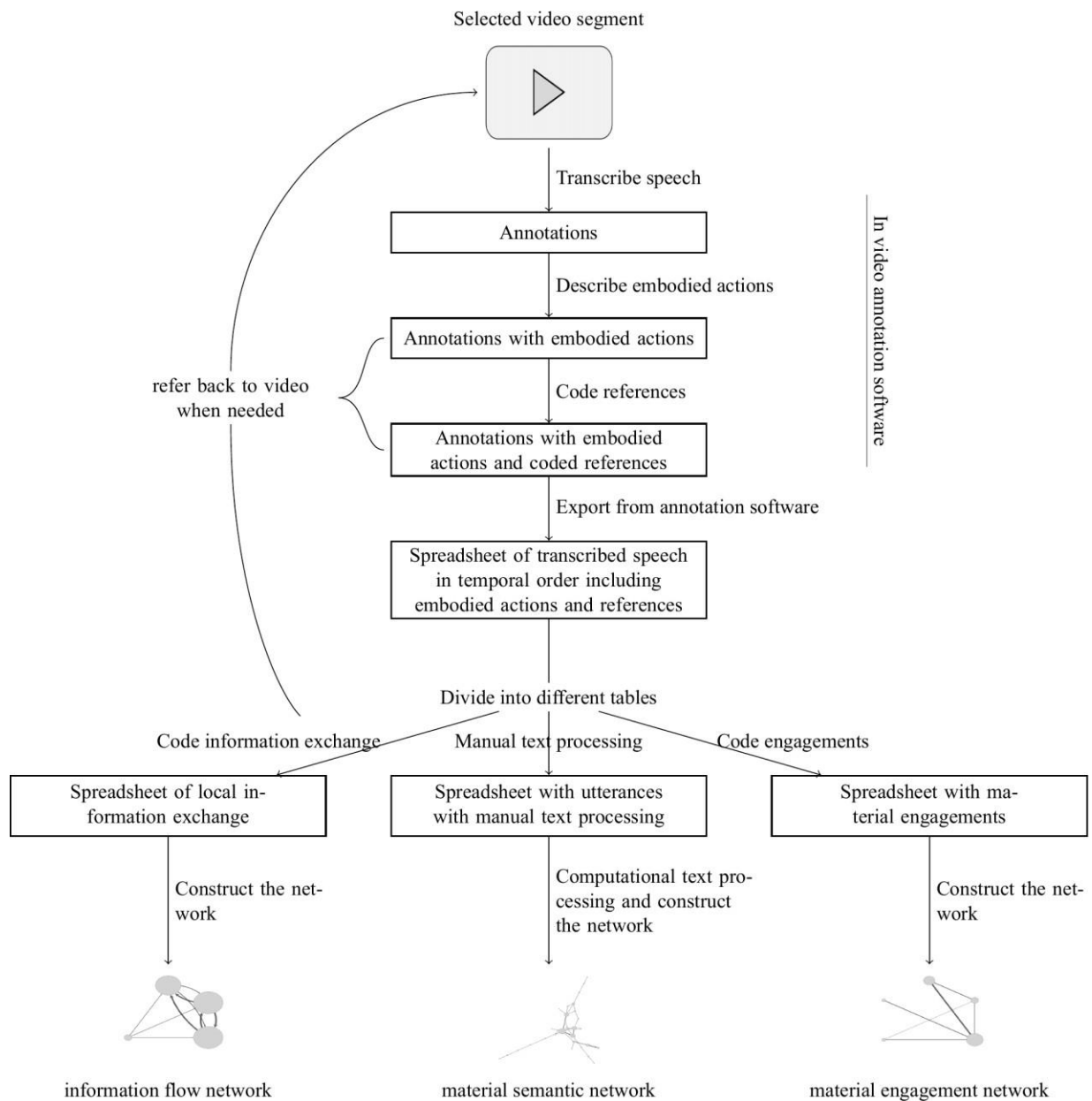
Selected video segment

Transcribe speech

Annotations

Describe embodied actions

Annotations with embodied actions

Code references

refer back to video
when needed

Annotations with embodied
actions and coded references

In video annotation software

Export from annotation software

Spreadsheet of transcribed speech
in temporal order including
embodied actions and references

Divide into different tables

Code information exchange   Manual text processing   Code engagements

Spreadsheet of local in-
formation exchange

Spreadsheet with utterances
with manual text processing

Spreadsheet with ma-
terial engagements

Construct the net-
work

Computational text pro-
cessing and construct
the network

Construct the net-
work

information flow network   material semantic network   material engagement network

Figure 2. Flowchart of the data processing.

Next, the annotations with the description of student actions and references are exported from the annotation software as a spreadsheet. This spreadsheet is then copied onto three separate spreadsheets for the different networks.

The individual spreadsheets are used to code information exchange, conduct the manual text processing and code material and verbal engagements. These are then used with network analysis software to construct the network data.

3.2 Video selection and annotations

The material for constructing the network data were obtained from videos collected as part of a larger research project in which project-based learning units of Newtonian mechanics were co-designed

with in-service teachers (Juuti et al., 2021; Schneider et al., 2020). The PBL units provided rich sources for student activities in which computers and laboratory equipment could play an active role in the knowledge construction.

Altogether, six focus groups of three to four students from five classrooms of two separate upper secondary schools participated in the study. The activities of each focus group were recorded with two small video cameras during the PBL units, which were six to seven lessons long. During the unit, students planned and investigated the motions of different objects, explored what causes changes in the motion, made models for the objects' motion with constant speed and acceleration, and constructed explanations. Video selection and analysis adapts the three-level approach of video-based research proposed by Ash (2007). At each level, videos are divided into shorter segments that are analysed in more detail. Here the first level constituted discrete phases of instructional activities that were observed and coded in real time by the researcher operating the video cameras. The raw video material (32 hours) was cut according to the coded phases of instructional activities, resulting in 16 individual cases of student investigations. One such case (duration of 13 mins) was selected for the analysis. The selection was based on video and audio quality, the clarity of student actions and lack of distractions for the students. The selected case is from the early stage of the PBL unit where three students, S1, S2 and S3, investigate the motion of a car on a track using computer-based data loggers and an ultrasound sensor. A sketch of the data collection situation is shown in Figure 3. After data collection, the students (S1 and S2) beside the apparatus (A) moved back next to student S3 by the computer (C).

Figure 3. 3D-sketch showing students' positions while they measure the speed of the car. While discussing the results, all the students are behind the computer C (yellow). The measuring apparatus, A, consisting of the track (red), the car (blue) and the ultrasound sensor (green).

The selected case was further divided into shorter, distinct segments of investigation subtasks identified from the video. These tasks were, for example, preparation, collecting data and interpreting data that were inductively identified from the video. There were clear transitions between these segments where the students, for example, agreed to move on from collecting data to interpreting results. Descriptions of each segment are given in Table 1.

Table 1

Segments of distinct student activities during students' investigations

Segment	Label of the segment	Description of the segment.	Length	Number of utterances
1	Preparation	Student S3, who owns the laptop, stays with the computer while the two other students move next to the apparatus (i.e., the track). Student S2 takes the ultrasonic sensor and holds it at the far end of the track. Student S1 takes the car and prepares to project it down the track it for the measurement.	24 s	15
2	Collecting data	The students measure the speed of the car three times as student S3 is not satisfied with the graphs from the first two attempts. The apparatus and the computer provide qualitative and quantitative information of the speed of the car.	1min 14 s	27
3	Interpreting data	The students discuss and interpret the graph. They ponder what to do next. The computer provides information of the measurement.	1min 17 s	43
4	Teacher support	The students ask the teacher how to analyse the graph. The teacher also gives additional instructions. The computer provides information of the measurement.	50 s	20
5	Analysing data	The students analyse the graph and discuss what the results mean and what number in the results box indicates the slope. The students discuss what they should analyse. The computer provides information of the measurement.	2min 36 s	60
6	Teacher support 2	The students ask the teacher which results are the slope and what else they should analyse. The teacher gives brief instructions. The computer provides information on the measurement.	39 s	20
7	Collecting data 2	The students take new measurements with the same set up and positions as in the first measurement. The second attempt is successful with the car clearly being projected faster than before. The apparatus and the computer provide qualitative and quantitative information on the speed of the car.	47 s	23
8	Constructing an explanation	The students construct an explanation after analysing the new graph and comparing the slopes of the graphs from the first and second measurements. The students arrive at the conclusion that with a higher speed the slope of the graph is greater. The computer provides information on the measurement.	2min 28 s	37

The third segment, interpreting data, was chosen for initial trials for constructing the network data before analysing the other segments. The segment was chosen so that it was not too short, had the fewest number of outside distractions, and seemed to contain all the necessary student actions and engagements, as detailed in sections 3.3.-3.5.

All three approaches (sections 3.3-3.5) to build the network data required annotations of the dialogue. Additionally, gestures and embodied actions were needed to interpret information exchange, the materials referenced and material engagements. For example, talk includes many demonstrative pronouns (i.e., this, that) that cannot be deciphered without gestures or embodied actions. The student talk was annotated using ELAN annotation software (2019). Next, different embodied actions and gestures were described next to the annotation in brackets, and finally the meanings of demonstrative pronouns were added in brackets next to the pronouns. An excerpt of the annotations is shown in Table 2.

Table 2

Excerpt of annotations from segment 3 Interpreting data. Student S2 was present but did not participate in the discussion.

	Student S1	Student S2	Student S3
1	That [part of the graph] is the first [part of the car movement] one		
2			Over here, here [part of the graph] it [the car], like, slows down [points at the computer screen]
3	All look at the computer screen in silence		
4			So, that [part of the graph] is it [part of the car movement] [points at the computer screen]
5	At this point [points at the computer screen] when it [the car] hits that end [points at the end of the track] it [the car] slows down		
6			Yeah
7	But then it [the car] starts to accelerate again when it [the car] returns		

In practice, the process of constructing the networks was iterative, namely, looking at the annotated data, going back to the video data and making notes and observations of aspects that needed to be included for constructing the network data. After the initial networks of segment 3 were completed, the practice of constructing the network data was applied to the other segments and revised where necessary.

3.3 Information Flow

Information flow can be used to characterise social or communication networks (Zweig, 2016). For example, people connected through social media can transmit information between each other or pass information from one to another. Similarly, online communication assumes an exchange of information. However, what this information is, is rarely explicitly stated.

Even if information is not explicitly defined, in written online communications building the network is straightforward. For example, nodes represent people and edges correspond to the messages between people. However, face-to-face communication differs from online communications. Face-to-face communication includes gestures and other non-verbal communication that are not possible in online communication. Spoken utterances are also generally shorter and more indecisive than online

messages. Additionally, dialogue contains small utterances that maintain the socially expected structure of the dialogue (Heritage, 1984). These are, for example, small agreements (yes, yeah). Thus, not all utterances contain relevant information for knowledge construction. Additionally, demonstrative pronouns with gestures like pointing can indicate information exchange that is not clear from the text alone. Lastly, student discussion might contain irrelevant talk. For example, the students might comment on some outside distraction.

The network based on information flow represents the exchange of information by having the students as nodes and edges. To build this network, consideration is first needed when to include an edge, meaning when information is exchanged between the actors. Information might have different definitions in different fields of science. In our case, meaningful information is connected to knowledge construction. While conducting the investigation, students need conceptual knowledge about the phenomena they are investigating, but they also need procedural knowledge concerning how to conduct the experiment. Thus, information is exchanged when the student's utterance, or utterance in conjunction with embodied actions, contains information related to the phenomena they are investigating (e.g., the first utterance of student 1 in Table 1), or how to investigate that phenomenon and the receiving person is present and not distracted.

Information exchange from the material world is more challenging, as materials continuously provide information. However, continuously tracking this information is impractical and therefore only clear instances of humans looking at the materials like the computer screen or the measuring apparatus are considered. Additionally, as the ultrasound sensor measures the distance of the car as a function of time, it transmits this information to the computer.
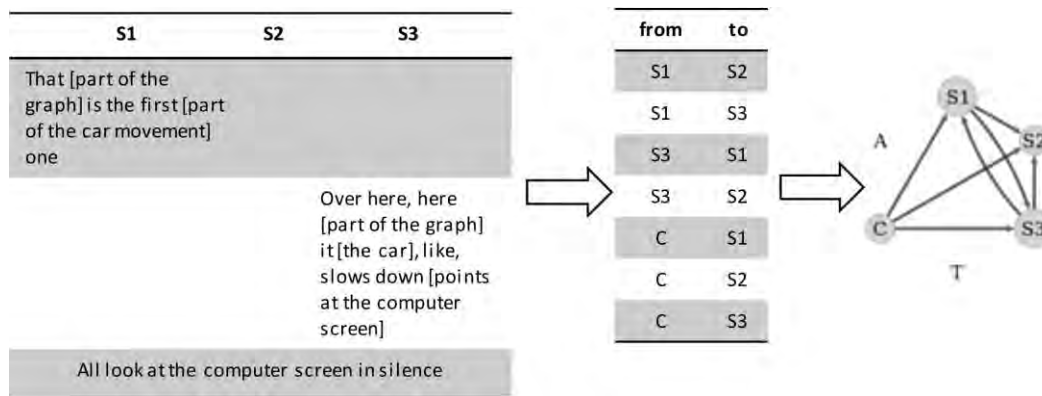

Figure 4. The process of constructing an information flow network.

The annotated dialogue with the embodied actions was used to code the information flow into a table on a from-to basis. An example of this, with corresponding network visualisation, is shown in Figure 4. Each row in the table is a directed edge between nodes (from left to right). The table, and thus the networks, may have multiple edges between them and therefore it is possible to construct weighted networks.

3.4 Material Semantic

A semantic network consists of words and the semantic connections between these words. Semantic connections can be found after text pre-processing that removes the structural features of the text. The pre-processing includes removing punctuation, converting capitals to lower case, and removing words that are used for the structure of the sentence rather than to carry meaning. The material semantic network was built on the ideas of thematic discourse network analysis introduced by Bruun et al. (2019). The thematic discourse network analysis used an iterative process that combines network analysis and qualitative discourse analysis to study students' group discussions. Qualitative discourse

analysis was used to revise initial semantic networks with the following steps: grammatical reductions to reduce all words referring to the same concept/meaning to one word, combine synonyms and treat slang words as synonyms, treat phrases as a single word and remove indefinite pronouns that do not carry meaning.

In addition to synonyms, we considered homonyms as they convey a different meaning even though the word has the same spelling. For example, the Finnish word 'aika' means 'time' or 'quite'. Thus, it was changed to a different synonym with the meaning 'quite' so as not to combine these two meanings with the same node.

During the dialogue, students refer to materials using demonstrative pronouns. For example, the utterance "Here it slows down" refers to the graph ("here") and to the car on the track ("it"). Therefore, to include the material aspects of the dialogue, all demonstrative pronouns that referred to some material aspect or physics knowledge were changed to those references.

In practice, to build the material semantic network from the annotated speech, we considered the following steps for text processing:

1. Replace demonstrative pronouns with the references
2. Grammatical reductions
3. Homonyms, synonyms and slang (spoken expressions)
4. Remove irrelevant utterances (e.g., reacting to outside distraction)
5. Remove punctuation and structural words (computationally).

After processing, the text network was built. Each distinct word is a node, and a directed edge is added between node A and node B when word B follows word A. Figure 5 visualises this process and shows the difference between the network straight from the text and after text processing.
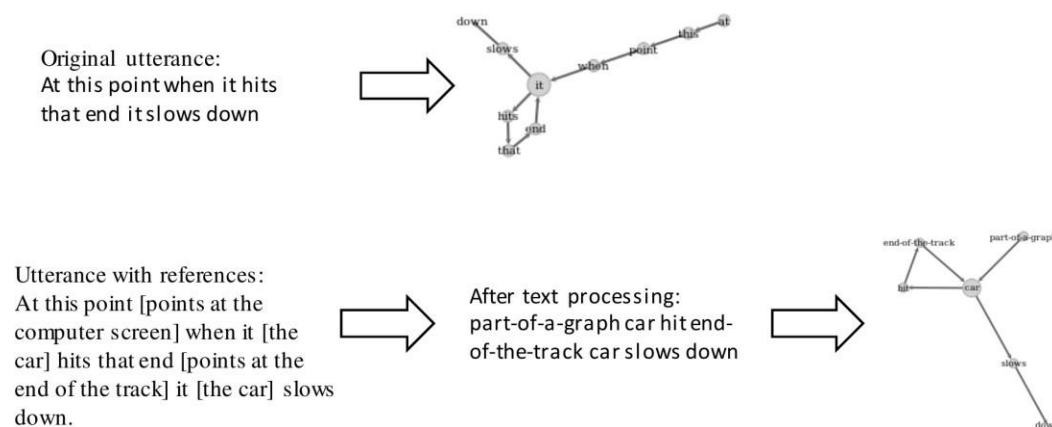

Figure 5. Example of a network without text processing (above) and a material semantic network constructed after text processing.

For the complete material semantic network, all unique words or connected phrases in the utterances are added as nodes. Then, edges are added between nodes from consecutive words within the utterances. Here again, there can be multiple connections between the same nodes as two consecutive words can be present in many different utterances and thus the network can also be constructed as a weighted network.

3.5 Material engagement

The material engagement network is built around the notion of intra-acting assemblages of the material-dialogic framework of Hetherington et al. (2018). As a network representation, an assemblage

would consist of human (i.e., students and teacher) and non-human (i.e., computer and apparatus) actors as nodes. Gradually, the assemblages form the material engagement network when the assemblages are formed and re-formed through the students' verbal and material engagements. Thus, the network has the students (and teacher), the computer and the apparatus as nodes just like the information flow network. The engagements are represented, however, by undirected edges as the engagement is shared between the actors without any meaningful direction for the engagement.

Human actors engage with non-human actors through embodied actions or references. In doing so, they form an edge between human and non-human nodes. Similarly, an edge between two human nodes is formed with verbal engagements when a student reacts to another student's utterance, giving additional voice to the dialogue.

Figure 6 shows an example of material and verbal engagements. The first utterance of student S1 contains material engagements with the computer and the measuring apparatus that the student points at and references. Next, student S3 verbally engages with S1 by agreeing and inviting student S1 to continue. Student S1 accepts the invitation and verbally engages with student S3, and again with the apparatus, by referring to the car.
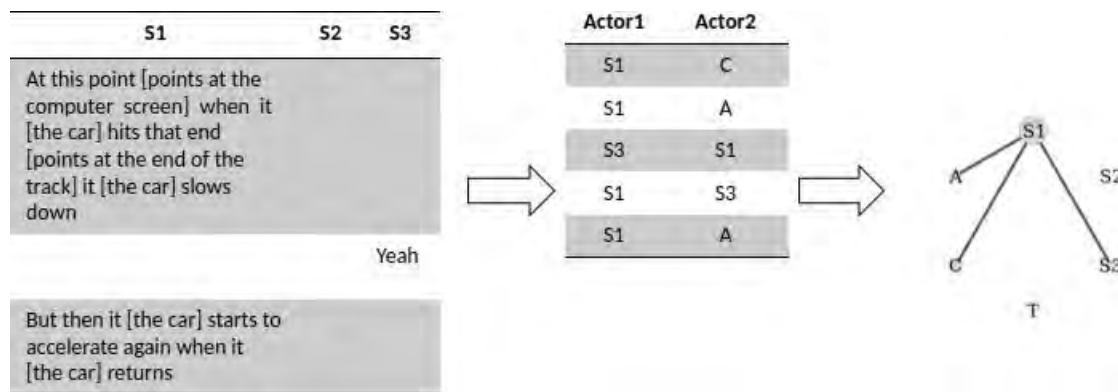

Figure 6. The process of constructing an information material engagement network.

The table with the material engagements is a collection of edges between nodes, as in the information flow network. Here there is no direction for the edges, but there may be multiple edges and therefore it is possible to construct weighted networks.

4. Constructed Networks

Three different types of networks were constructed for each eight segments (Table 1) from the video segment of the students' investigations. All networks were constructed as weighted networks and node strengths were calculated for each node in each network. The node strength is the sum of the edge weights connected to the node (Barrat, Barthélemy, Pastor-Satorras, & Vespignani, 2004). The networks were constructed and visualised from the tabulated connections and the processed text using Python and the graph-tool module (Peixoto, 2014).

The 24 visualisations of the networks are shown in Figures 7-10. For the information flow and the material engagement networks, the nodes are labelled by the actors: S1, S2, S3 are the students, T is the teacher, C is the computer the students used, and A is the apparatus that includes equipment used for the investigations (i.e., the track, the car and the ultrasound sensor). The nodes in the material semantic networks represent individual words or references, with the strongest (highest strength) nodes labelled with the corresponding words translated from Finnish. The weight of each edge is represented by the edge width. Similarly, node size is determined by the node's strength. The layout for the

information flow and the material semantic networks is similar, with nodes arranged into a circular pattern with the same order throughout. The layout of the material semantic networks is based on the Fruchterman-Reingold spring-block layout (Fruchterman & Reingold, 1991).
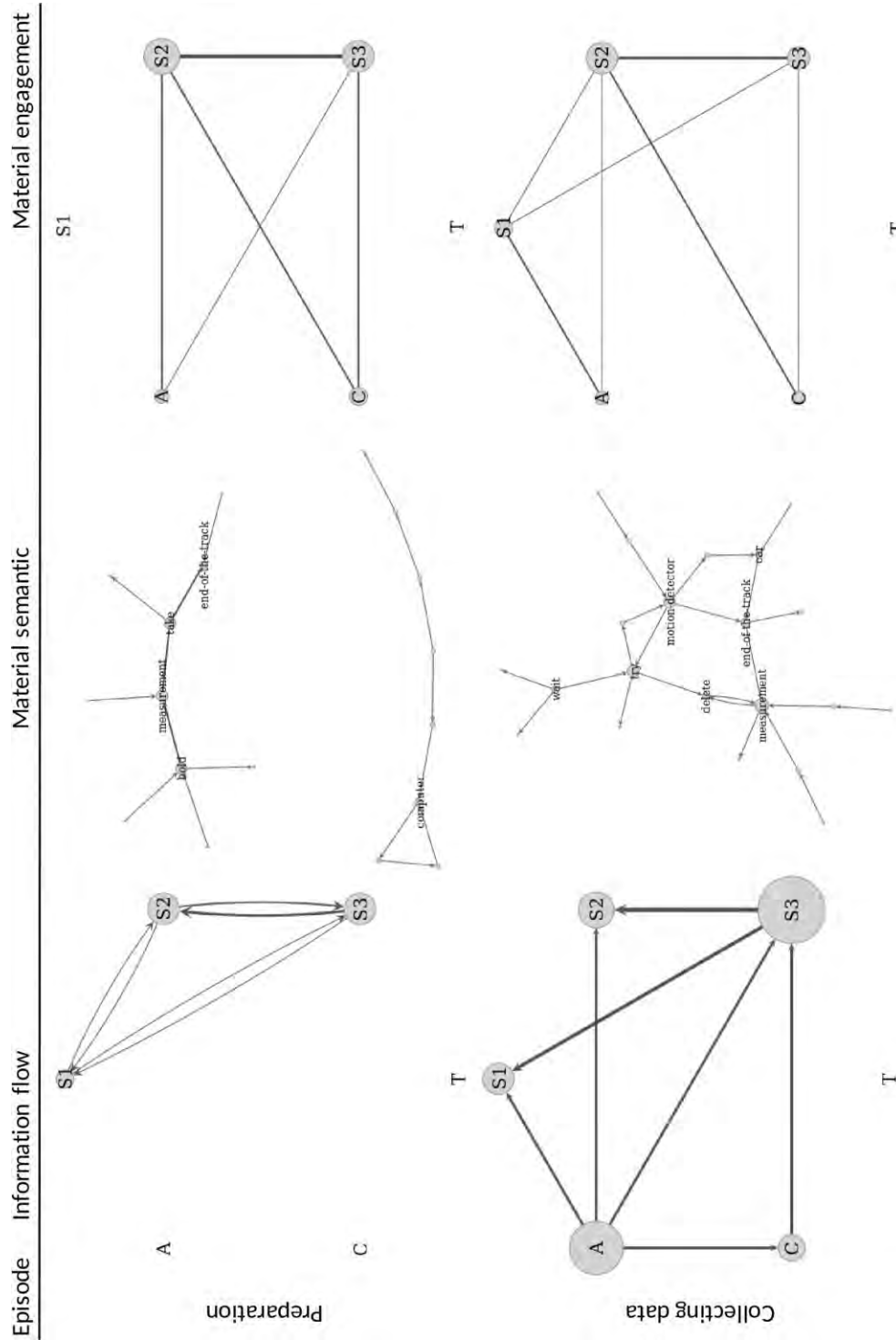

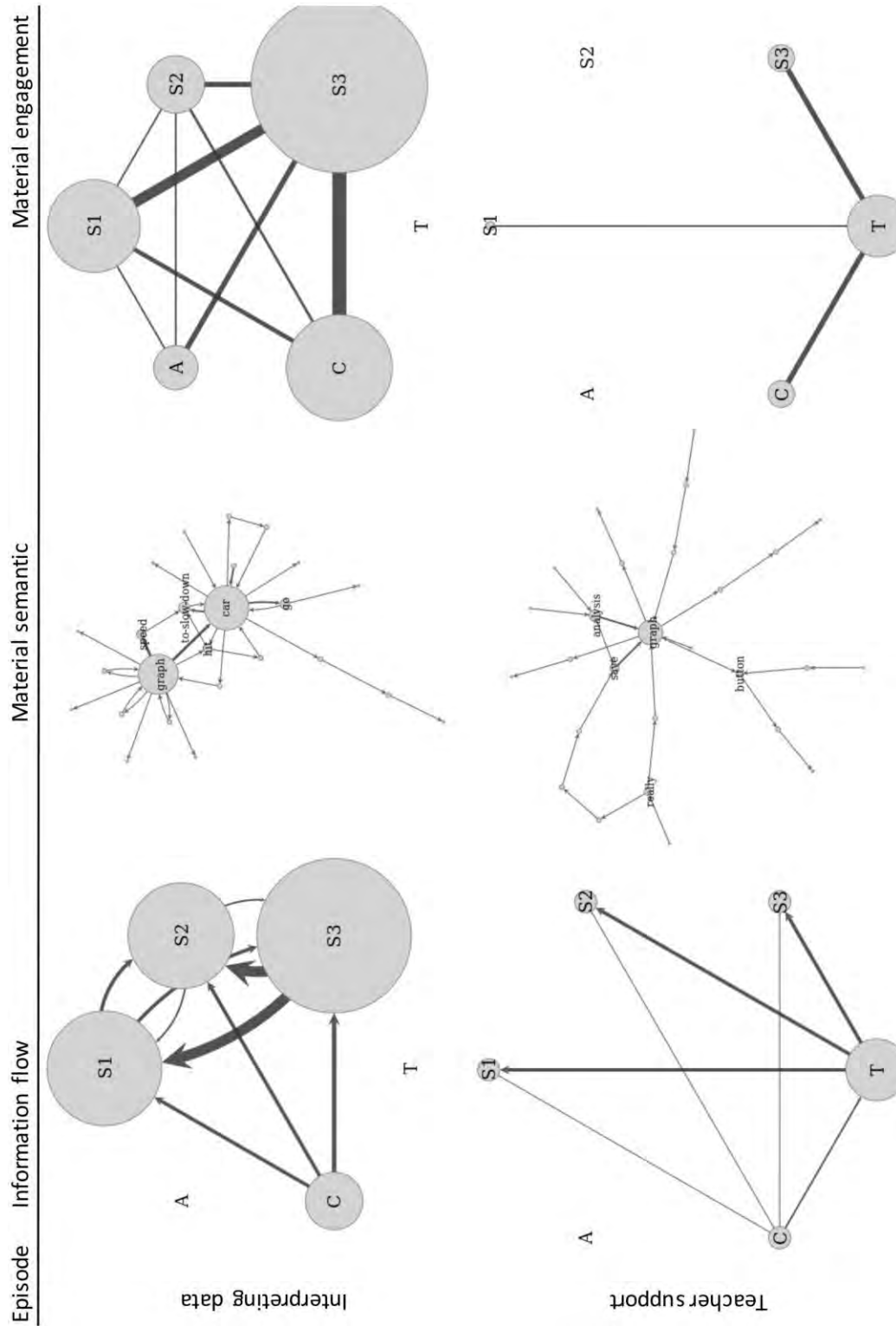*Figure 7*. Visualisation of the different networks from segments 1 and 2.

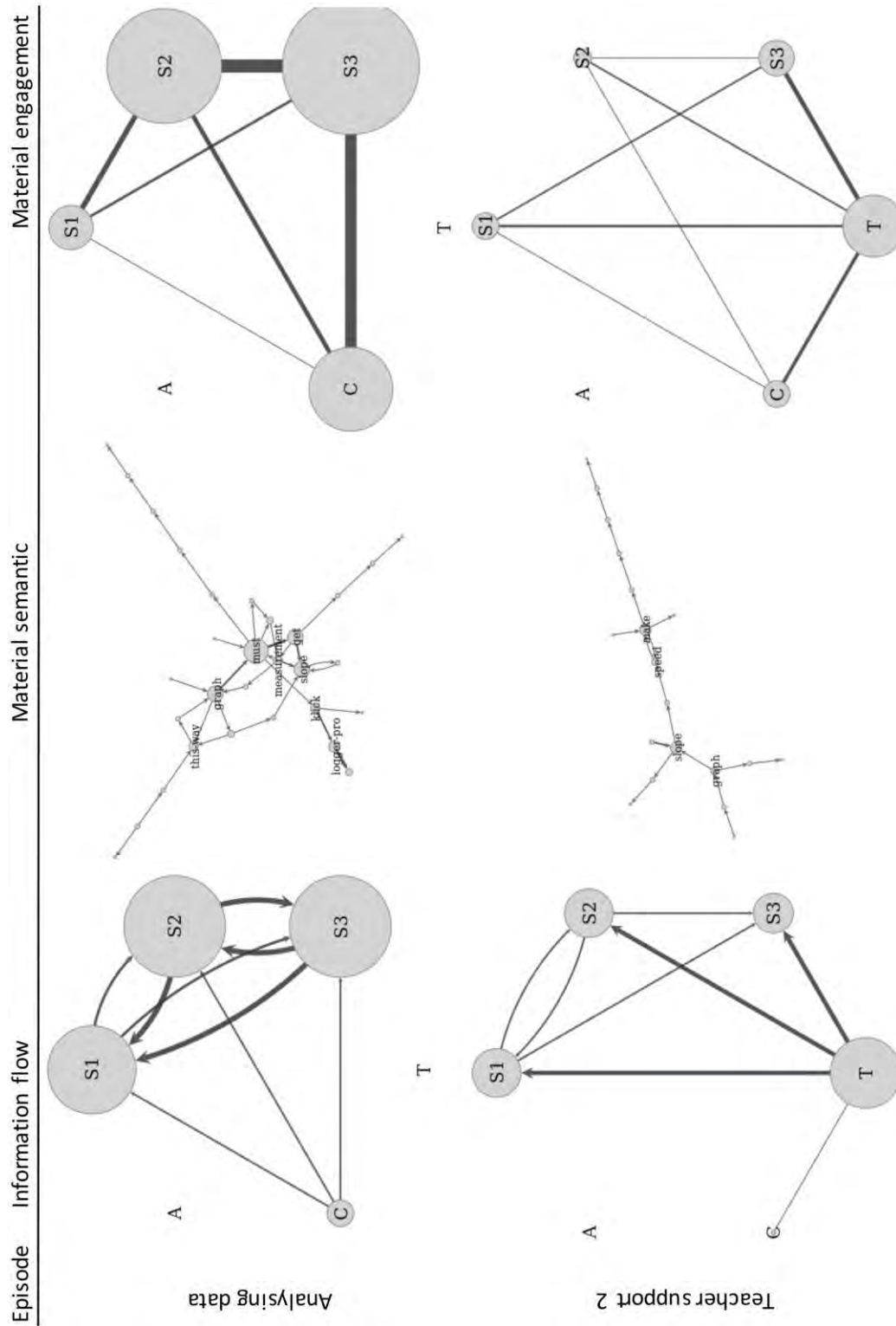*Figure 8.* Visualisation of the different networks from segments 3 and 4.

Figure 9. Visualisation of the different networks from segments 5 and 6.
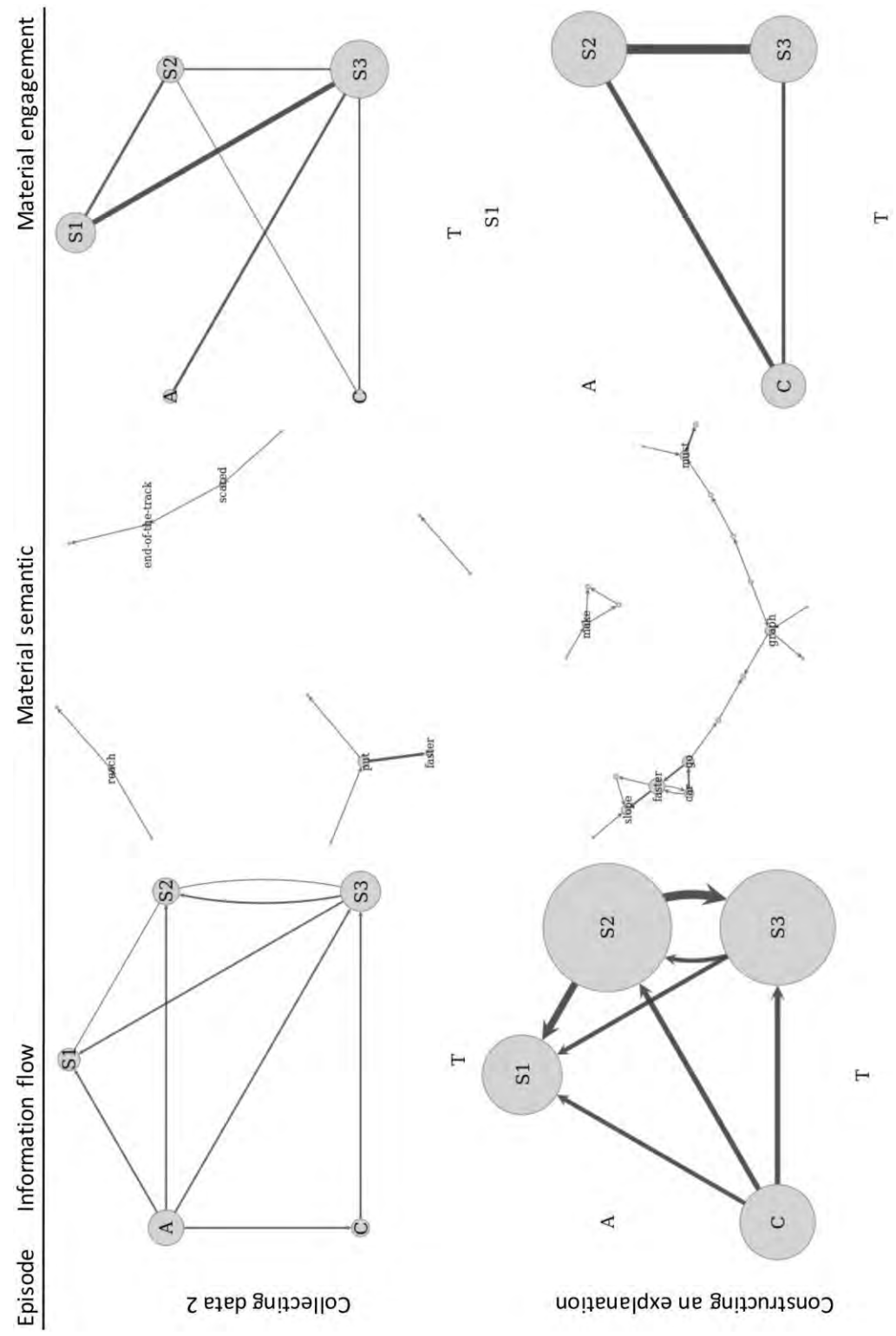
Figure 10. Visualisation of the different networks from segments 7 and 8.

The information flow networks show how information was exchanged locally between the different actors. Information was received from the measuring apparatus and the computer and exchanged between humans, creating an overall flow of information within the network. *Collecting data* shows clearly that student S3 receives information both from the apparatus and from the computer, whereas the other students only receive information from the apparatus. The student S3 also passes on

the information from the computer screen to the other students. It seems that it could be beneficial for the student to see the phenomena on the measuring apparatus simultaneously with the graph on the computer screen as this allows more opportunities to exchange information and engage with other actors resulting in the strong nodes for student S3.

The material semantic networks show the semantic content of the student dialogue and reveal the strongest semantic connections. The material semantic networks of *preparation*, *collecting data 2* and *constructing an explanation* are separated into two or more components that are not connected with each other. This results from the dialogue having utterances that do not share semantic connections with each other. For example, during *the preparation* the students did not semantically connect the measuring apparatus and the computer. However, these were connected while doing the measurement, as can be seen in the corresponding semantic network of *collecting data* in Figure 7. In the other two cases, it is possible that the small components separated from the main body of the network are single utterances that while task related are not taken into part of the discussion as a whole. It is also possible that collecting data for the second time, the students did not need to discuss about conducting the measurement as each student's role was the same as before, and thus there was little or no need to consider who does what and how. Similarly, in the last segment the smaller component is a single utterance about scaling the graph that is not an important part of interpreting the data and thus does not semantically connect with the discussion about the slope of the graph and the motion of the car.

When the students discuss the results, the main content seems to be the connection between the graph on the computer screen and the car, but not the physics concepts relating to the two. Even in the final segment when students are able to connect the slope of the graph with the speed of the car, they do not use the word 'speed', instead, they use the phrase 'goes faster'. This shows that even though the students can connect the phenomena with the measured results, they do not yet use the appropriate physics terminology.

The material engagement network shows what the students and the teacher were engaging with during the investigations. During *interpreting the data*, student S3 is more strongly engaged with the computer than the other two students. Overall, the engagement between students S3 and S1 is strongest, but in *analysing the data* the engagement is strongest between students S3 and S2. In the final segment, student S1 is not engaged at all, and the only engagement is between students S2, S3 and the computer when these two students are discussing the results of the analysis.

In general, the teacher, when present, has a very clear role. The teacher receives information from the computer screen and gives information to the students. The material semantic networks are quite small and simple, and this probably results from the segments being short and there not being much dialogue, as the students are mainly listening to the teacher. However, the node representing the graph on the computer screen is strongest, showing that the semantic content in these situations concerns the graph. The engagement of the teacher is mainly with the computer and the student using the computer (student S3). Thus, when the teacher is present, he/she receives information about the graph, engages with the student using the computer and gives information. In practice, the teacher sees what stage the students are at and gives guidance for continuation.

Preparation has the simplest networks of all the segments. It is possible that the network approach is not suited to this kind of student activity, but more likely the students did not need to do much preparing as the measuring apparatus was set up by the teacher previously and there was not much to do for the students other than to conduct the measurement. If they had needed to plan the investigation, and build the apparatus to conduct the measurement more precisely, the networks might be very different.

Lastly, information flow and material engagement networks in Figures 7 to 10 are similar, but the flow network shows the direction of information, so it represents the students' activity differently. For example, in the final segment, *constructing explanation*, student S1 is not engaged with other actors yet is receiving information. Thus, student S1 is a passive participant in the final discussion about the analysed results, showing that the student is not part of the intra-acting assemblage

5. Discussion

Currently, science education research within a new materialist frame is still in its early stages. Theoretical work has been carried out formulating the material-dialogic approach (Hetherington et al., 2018) and some empirical studies have applied the approach (e.g., Cook et al., 2019; Hetherington & Wegerif, 2018). Milne and Scantlebury (2019) have discussed materiality and material practices more broadly in science education. The growing use and interest of network analyses in science education research led us to explore how network analysis could be applied in authentic classroom learning where the role of materials, such as laboratory equipment, is acknowledged.

The main aim of this study was to develop and demonstrate methods for constructing network data from video, using the materialist perspective to take into consideration the materials present in science investigation situations. Instead of resulting in a single network approach, we identified three possibilities that were then developed with the video sample from the physics lesson. The resulting networks show clearly that network approaches can be used to study the learning processes where students are engaged in investigations connected with materials for learning science knowledge and skills. For example, in this case the most worthwhile activities seem to be when students are analysing the data or discussing results. Then the students are exchanging information and engaging with the materials and each other. This results in strong (large) nodes with heavy (wide) reciprocal edges. Moreover, the semantic networks are more complex than at other times.

In order to better understand the role of materials in learning, we grounded our approach to Network Analysis and a New Materialistic frame. The resulting method resembles Interaction Analysis (IA) that investigates the interactions between humans and the objects around them. IA considers human talk and non-verbal communication and aims to identify practices, problems and solutions (Jordan & Henderson, 1995). IA even has a material perspective as it sees interactions situated in the material world and considers how humans use artefacts and technology. However, IA is interested in the achievement of social order and "how people make sense of each other's actions" (Jordan & Henderson, 1995, p.41). This is where the methods diverge. Whereas both methods focus on interaction, we construct network data appearing through interactive actions of different actors as seen in the video, in contrast to trying to understand the moment-to-moment construction and maintenance of social order. This allows the use of several network analysis methods to quantitatively investigate different aspects of collaborative learning with a materialist perspective. Thus, the research aim, to use cases and data constructed from video, are different between the methods.

5.1 Limitations and possible improvements

Constructing the information flow network involves uncertainty, as coding the information exchange is challenging in face-to-face communication. There is always some need for interpretation, even if the student talk is taken per se. For example, interpreting student embodied actions or material references can be challenging. Moreover, there is no distinction between different information or the amount of information per utterance, therefore edge weight does not necessarily represent the quality or quantity of information. Similarly, material entities continuously transmit information, making identifying and selecting instances of information exchange challenging. A more detailed coding framework and analysis protocol could improve the interpretation, but it would result in more manual work.

Additionally, it should be noted that the strength of the nodes cannot be directly interpreted as more flow or a stronger engagement as the longer video segments contain more information exchange and engagements; thus, they the nodes appear stronger in the network. It would be possible to normalise

the networks with the number of connections or length of time to gain more comparable results. However, at least for information flow, information content and thus the amount of information differs from utterance to utterance, and this should also be taken into account if edge weight is to be equated one-to-one with information. This would require a strict coding manual for information and would also require additional work and time spent on the coding. This additional work might not significantly improve the results, as the structures and patterns of the information exchange are more compelling than the exact amount of exchanged information. We considered information relating both to conceptual and procedural knowledge to be relevant information. It could be possible to separate and build networks relating to both types of knowledge that might reveal additional details of information exchange. However, the two knowledge types are not clearly distinguishable from each other, and relating the knowledge types to information within a single utterance might be unfeasible. However, the material semantic networks can distinguish the overall tendency for the type of knowledge. For example, while collecting the data, the strongest nodes are *motion detector, end-of-the-track,* and *measurements*, indicating that the students are discussing how to conduct the measurement using the motion detector at the end of the track. Conversely, while interpreting the data the strongest nodes are *graph* and *car*, showing that the semantic content is the connection between these two.

When constructing material semantic networks during the text pre-processing, different steps might be easier to do manually than computationally and vice versa, depending on the tools available and on the language of the actors. For example, speech-to-text automation could help with the annotations as so-called first pass transcripts (Moore, 2015) before the manual work of identifying speakers and coding the embodied actions and material references. Similarly, eye-tracking technology would enable coding actors to gaze precisely and would help in identifying instances of receiving information from the materials. This would also allow identification of different parts of materials as nodes like, for example, the parts of a graph or the components of the measuring apparatus. Concerning the aims of our study, eye tracking was not applied as we wanted the method to cause as little disruption to teaching and learning as possible, and the technology was not mature enough for straightforward deployment. Similarly, text-to-speech was seen as unnecessary for the relatively short video segments, especially as the technology in Finnish was not reliable enough at the time. However, in the future, with a larger research setting, use of one or both methods could be a major improvement.

There are also some practical technical limitations to this method. For example, even with two video cameras not all student actions were clearly visible as they can be obstructed by other students or material objects. Similarly, student speech can, at times, be indistinct or ambiguous. However, these challenges are more about video-based research in general and can be addressed by using good practices and appropriate equipment (Derry et al., 2010). Here the video material was collected from an authentic classroom setting, where there are always trade-offs with camera placements (Erickson, 2012). Moreover, there is always some degree of external sounds, noises and other distractions in authentic classrooms that affect the video and audio quality. A more controlled setting (e.g., a teaching laboratory) would provide clearer video material that could be used with the automated techniques mentioned above.

5.2 Recommendations for future research

The networks can be interpreted visually, but they could also be analysed more explicitly with the many different tools that network analysis offers. The analyses could show, for example, the roles in the information exchange, individual contributions to overall semantic networks, or what intra-acting assemblages students are part of. Thus, different network approaches and analyses could be used to answer different research questions concerning science learning. For example, combining background information or pre- and post-test scores would allow one to correlate learning with the roles of information exchange and explain how prior knowledge affects the roles or what effect the roles have on learning. Similarly, it could be asked how prior knowledge or experiences affect contributions to the material semantic network. Prior experiences with investigations might determine engagements with materials and it could then be asked who uses the materials during investigations and why.

Of the individual network approaches, the material engagement network approach seems promising applied within the material-dialogic framework of Hetherington et al. (2018). In essence, the networks are a collection of intra-acting assemblages of the framework. These assemblages could be equated with network motifs. It would be possible to compute different motifs and thus ascertain what kind of assemblages are present.

Computing the network roles from the information flow network could show each individual's role in the information flow. Network roles are directed motifs and include, for example, source, sink and relay (McDonnell et al., 2014). Finding the roles of each actor (human and non-human) could reveal the students' abilities and the impact of material elements. For example, a student who is a source or who relays information should be more crucial in the knowledge construction of the group.

Currently, the material semantic network does not differentiate the individual actor's contributions. For example, the material semantic networks of teacher support are built almost entirely from teacher talk. However, this talk is not explicitly represented in the network. Additionally, aggregating the material semantic network into one network and using multidimensional network analysis methods, it would be possible to separate each student's and teacher's contribution to the overall material semantic network. Understanding each student's contribution is an important part of the evaluation. Moreover, understanding how individual students contribute to the overall knowledge could be used to guide formative assessment practices. Additionally, understanding what or how teachers contribute to students' knowledge could show the role the teacher has while supporting the students.

The advantage of network analysis is that it provides an opportunity to analyse large and complex datasets. Therefore, the future applicability of our method depends on its scalability. Although including materiality requires manual coding, the ongoing development of text-to-speech automation promises easier initial steps for constructing the network data and thus makes constructing larger datasets easier. Similarly, machine learning technologies could be used to automate part or all of the manual coding required. Here we have demonstrated the steps required to generate the network data from video material. Currently, some of these steps were automated and more can be automated in future. Thus, scaling the construction of network data should be possible in subsequent studies.

Finally, a targeted collection of video material could be used. For comparative study, for example, it would be possible to first measure background variables and use that information to select different kinds of groups for video recording. This would limit the amount of video material and ensure high contrast between analysed cases.

6. Concluding remarks

In this study, we introduced a method to build a network data of human and non-human actors using video. Using a network analysis review and a new materialist theoretical background, we identified three possible approaches to constructing network data. Additionally, a real-world video was used to refine the approaches. The three approaches are the information flow network, the material-semantic network and the material engagement network. Each network has its benefits and drawbacks and ultimately an approach combining two or all three networks might be preferred. However, we have shown here that it is possible to build network data from video within the new material perspective. The production of these networks allows the use of network analysis methods to investigate aspects of collaborative learning where the role of materials has been taken into consideration. This work responds to the demand of including materiality in science education research (Milne & Scantlebury, 2019), contributes new materialist methods to research in education and expands possible methods for a material-dialogic framework. In conclusion, the proposed method allows studies into the material and dialogic relationships that emerge when students are engaged in investigations in school.

Keypoints

- New materialism and network-based approaches have gained interest in educational research.
- The aim was to combine these two approaches into new materialist network approaches to study students' investigations.
- Three possible approaches were identified and developed with a video sample from an upper secondary school.
- The approaches are: 1) information flow, 2) material semantic and 3) material engagement.
- The developed approaches are applicable for future research.

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