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RESEARCH ARTICLE

The influence of external concept structures on an individual's knowledge structures

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Abstract

This experimental investigation considers how the inherent conceptual structure of external representations influences individuals' knowledge structure, and in addition proposes a measure of global collective knowledge to account for the influence of pre-existing knowledge structure. In two studies, undergraduates in a hospitality management course completed a pre-knowledge structure (pre KS) measure, a prior knowledge pretest, then read parallel versions of either a text or a table about the Internet of Things, then completed a post knowledge structure (post KS) measure, and finally completed a comprehension posttest. Analysis of the comprehension posttest data showed that the text group significantly outperformed the table group ($p < .05$) mainly due to performance on factual and main idea items, but not inference items. The pre- and post-KS data were analyzed as Pathfinder networks. Descriptive comparisons of between group networks (group–group) and within group networks (pre-post) showed that the table and text between-group networks were quite alike before reading and were even more alike after reading (i.e., peer convergence of local collective knowledge structure). The within-group network overlap from pre-to-post was also substantial. In addition, pre-to-post similarity with the expert shows the *text* group networks became more like the expert referent but the *table* group networks became less like the expert referent. Exploratory findings for this global collective knowledge network approach based on Google Ngram frequency dependencies were partially supported. For theory building, the results show how the influence of external representations can be framed in terms of a representation's inherent conceptual structure. For practice, this list-wise measure for eliciting knowledge structure provides a quick way to elicit individual and group-level knowledge structure networks that can be used in ordinary classrooms for formative and summative assessment.

Keywords Tables and texts · Knowledge structure · Collective knowledge · Pathfinder networks · Comprehension

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Introduction

Jonassen (1988) notes that "Learning may be conceived of as the mapping of subject matter knowledge (usually possessed by the teacher or expert) onto the learner's knowledge structure." (p. 13) Knowledge structure (KS) here refers to the organization of ideas in individuals' memory and in language artifacts. These artifacts are external representations of subject matter knowledge, such as text, tables, and graphics. They are used to "…facilitate construction of deeper knowledge structures in the internal representational systems of the learners." (Kollar & Fischer, 2004, p. 113). This investigation proposes that the inherent knowledge structure of lesson artifacts is an important and overlooked factor in learning with external representations that may account for the effect of the representation (Schwonke et al., 2009; Shavelson, 1972).

This investigation takes a fresh look at how the inherent concept structure of external representations of table and text (Fiorella & Mayer, 2016; List et al., 2020; Mayer, 2009; Schwonke et al., 2009; Shavelson, 1972) along with pre-existing knowledge structure (pre KS) influences individuals' comprehension posttest performance and post knowledge structure after reading (McNamara et al., 1996; Teplovs & Scardamalia, 2007; Zhang et al., 2018). In addition, two new measurement approaches are explored, (1) a Google Ngram frequency dependencies method for establishing a global collective knowledge network of the text content and (2) a list-wise measure of individuals' KS with Pathfinder network scaling to represent readers' KS of the content before and after reading.

Tables, also referred to as a matrix by Robinson and Kiewra (1995), organize textual information into rows and columns, typically with row and column headings, although the form of a table is not universally standard. A table's form and structure can differ substantially from an equivalent text in at least three ways: *content*, *structure,* and *function*. Wang (2016) notes that "The content of a table is a collection of interrelated items, which may be numbers, text, symbols, figures, mathematical equations, or even other tables." (p. 2). Perhaps any content can be presented in a table, however, in practice, the type of domain content can constrain how content is displayed as a table.

Beyond content differences, the *topic structure differences* between text and table is an important aspect of tables that is essential to understand a table. Wang (2016) notes that table content tends to be denser because more information can be represented in the same space while maintaining important details. The typical spatial nearness of topic structure and concepts in tables compared to text matters because forming inferences is easier when related concepts are spatially near (OECD, 2011). The third important characteristic of a table is its function which intimately relates to its structure, "…to present detailed information in a compact way such that the ability to search and compare the information is enhanced" (Wang, 2016, p. 5). Establishing a row-column structure in memory could support mental search.

To read a table, the reader must attend to the table structure. Understanding the information in a table as the author intended generally requires additional, or at least different, effort relative to reading the same content in a traditional text form (Wright, 1980). For example, imagine a text separated into sentences that are then randomly reassembled, reading the sentences in a different order would most likely lead to a different understanding of the content (Einstein et al., 1984; Poindexter & Clariana, 2006). Similarly, reading the content in a table idiosyncratically is quite likely and would lead to different understandings of the table content. So how does reading a text and reading a table differ?

Comprehending text and tables

Reading comprehension involves complex and varied constructive mental processes (Goodman, 1986) such as letter perception, recognition of words, detecting the meaning and function of words in the text—while simultaneously connecting and integrating the meaning of the text with one's prior knowledge. These are all involved almost instantaneously for typical readers and involve the interrelationship between reading and the conceptual structures of the author, of the text, and of the readers of that text.

Kintsch (1992) and Van Dijk and Kintsch (1983) described three concurrent conceptual representations of cognitive processing of texts, a surface representation, a propositional text base, and the situation model. The *surface structure* represents the literal words read as automated lexical and syntactic processes in a fairly linear-sequential way (although not necessarily read in the same order as written due to saccade skips and regressions). The *text base* is a relational network of derived propositions in the text, and the *situation model* is the reader's interpretation of the text that is the reader's unique, idiosyncratic model of the text that is reflective of the reader's prior knowledge. Text spatial layout features, including sequential linearity, parsing into sentences and paragraphs, titles, and headings to show the topic structure and extra-text signals such as underlining and italics to direct attention and support automatic inferences influence reading comprehension. Familiarity with these text features gained over many varied reading experiences (i.e., descriptive, expository, persuasive, narrative, technical, and poetic genres) will determine how a text is read by each reader (Kintsch & Yarbrough, 1982; Schnotz, 1984, 1993).

How can table form influence reading comprehension? A table is a text form that obviously offers very different layout features than other text genres. A table has been described as a descriptive rather than depictive representation (Rolfes et al., 2018; Schnotz & Bannert, 2003), so a table and text are somewhat more similar to each other relative to other external representations such as graphs, bar charts, and pictures, because both text and tables are descriptive according to Schnotz and Bannert (2003). However, for tables, readers must realize the structure of the table at the surface level, where the structure and semantic content are preserved at a text base level as a connected network of propositions, and then interpret it as their situation model based on their prior knowledge.

Wright (1980) describes additional processes when reading tables beyond reading a text. Readers must first determine the table format and how the components are interrelated and then use this "table knowledge" to acquire the table. In other words, while reading a table, a reader converts the table content into a linear read sequence. In cases where readers can access the posttest while reading, they can scan the table or text for each posttest item, then in that unusual case their knowledge structures of the content would be fragmented and more aligned to the test rather than to the table or text.

Figuring out the roles of columns and rows then is necessary for comprehension. Readers need to know if they should read across each row first or read down each column first (Frase, 1969), and table spatial layout has been shown to alter this approach. For example, white space between rows leads to row-by-row reading while white space between columns leads to column-by-column reading (Ideno et al., 2020; Shimojima & Katagiri, 2012). Also, when reading a table, do readers continually glance at the row and column headings (e.g., reinforcing the text topic structure), only infrequently use these, or not even notice the headings?

A text and a table of the same content will almost certainly place the key terms (topics and concepts) in different locations on the page or screen. Page layout is used by both the language and the visual-spatial processing systems; this is important because the visual-spatial system forms a "cognitive map" of content location. That is, readers make controlled rather than random lookbacks of already read text (saccade regressions) and this internal Euclidean mental map of the content that can guide lookbacks also will likely influence ongoing comprehension.

For example, in an imagined text (see Fig. 1), the concept A1 is closer to concept A2 and further away from concept B1, while in the table, A1 is equally close to A2 and B1. So, an inference that combines A1 and B1 should be relatively easier for the table reader. This visual-spatial cognitive map of the actual concept locations as well as the inherent knowledge structure network of the information both influence processing to the degree relative to the task requirements (Peer et al., 2021).

Mangen et al. (2013) note that during reading, "… integration requires that the reader has constructed a solid mental representation of the structure of the text." (p. 66). Therefore, since reading comprehension for tables needs extra processes or at least a less familiar process, then the mental representation of the structure derived from reading a text or table will likely be different in ways that will influence comprehension.

Measuring knowledge structure

Research in internal cognitive processes and systems is of theoretical interest in educational research (Ifenthaler, 2010). Here, knowledge structure (KS) is a hypothetical construct referring to the association of concepts in long-term memory, meaning depends upon the structure of mental constructs (i.e., also called cognitive structure, mental models, schemata, structural knowledge, structural networks, Gagne, 1985; Jonassen et al., 1993; Quillian, 1968; Rumelhart, 1980).

However, as those internal representations are not directly observable, there has been much effort to develop valid instruments and methodologies to reproduce them. For example, SMD Technology (Ifenthaler et al., 2007) is an automated tool to assess individual KS development processes by observing Surface, Matching, and Deep structures. Ifenthaler et al.' further created a web-based integrated set of assessment tools called

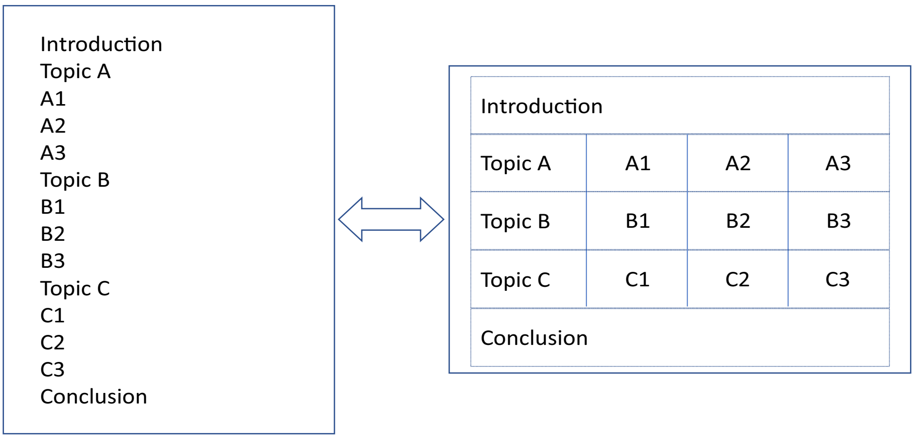

Fig. 1 Example text (left side) and table (right side) content layouts of an imagined text to show the different concepts' spatial locations

Highly Interactive Model-based Assessment Tools and Technologies (HIMATT) to measure changes and analysis when learners are involved in complex problems (Pirnay-Dummer et al., 2010). This tool includes three tools for different purposes: DEEP (Spector, 2006; Spector & Koszalka, 2004), T-MITOCAR (Pirnay-Dummer et al., 2010), and SMD (Ifenthaler et al., 2007). T-MITOCAR can visualize knowledge based on the structures and meanings of the words and their uses in text sources. For example, Gogus (2013) used this HIMATT tool in a mathematics course to investigate mental models of individuals and groups during problem-solving tasks comparing novice models with expert models.

Another tool to represent KS is a computer-based text analytic software system, *ALA-Reader* (Clariana, 2003), used and tested in various learning environments across several languages (e.g., Arabic, Dutch, Chinese, English, German, Korean). *ALA-Reader* representations can clarify knowledge gaps and misunderstandings (Clariana, 2010; Jonassen et al., 1993; Ntshalintshali & Clariana, 2020) or, as in this investigation, it can be used to visualize the text and the table readings as a way to capture and represent these external representations.

The current investigation uses a new *list-wise* multiple-choice approach adapted from Ntshalintshali and Clariana (2020) to elicit KS before and after reading. Each list-wise item consists of a keyword in the stem and all the other keywords as options. For each item, the reader selects two words associated with that keyword. In this investigation, there are 12 key terms and so there are 12 multiple-choice items. Because all the key terms are included in every item, the full context of the content is present at each responding instance, this may be optimal because the loss of context (i.e., mind wandering) has been suggested as a problem for some other elicitation approaches such as free recall (Clariana, 2010, p. 46). This list-wise approach is a reasonably quick way to elicit KS that can be implemented with ordinary test software, and especially, it is simple to accomplish in Qualtrics.

After this elicitation process, the participants' list-wise data are converted to Pathfinder networks (Schvaneveldt, 2004; Schvaneveldt et al., 1985). Pathfinder network(*PFnets)* analysis is a rigorous data reduction approach that is believed to capture the most salient semantic structure of data and disregards the rest. Jonassen et al. (1993) noted that *PFnet*s are better for representing local comparisons between terms, so are ideal for this list-wise data. In this investigation, the text and table artifacts were converted to *PFnet*s using *ALA-Reader* software that converts written text directly into proximity files (prx). *PFnets* software was used to convert these proximity data to network representations of text and table to compare these to the structures derived from the individuals list-wise responses (both pre and post reading).

Group-level collective knowledge structure

Pathfinder software has an Average Proximities feature that can establish a network of a group's collective knowledge (i.e., local collective knowledge, Teplovs & Scardamalia, 2007). Clariana et al. (2019) proposed that externalized global collective knowledge (Clariana et al., 2022; Hecker, 2012; Nonaka, 1994) could partially account for local collective KS. In their investigation of the role of sentence breaks on knowledge structure, participants (n = 150) were asked to read a 300-word expository text on global positioning satellites presented either sentence-by-sentence or as a full paragraph, and then complete a vertical sorting task. The sentence and paragraph participants' group-average KS networks were quite alike, with a 77% link overlap (see bottom panel of Fig. 2). Google Books Ngram viewer was used to generate a network of 12 key terms from the text as one

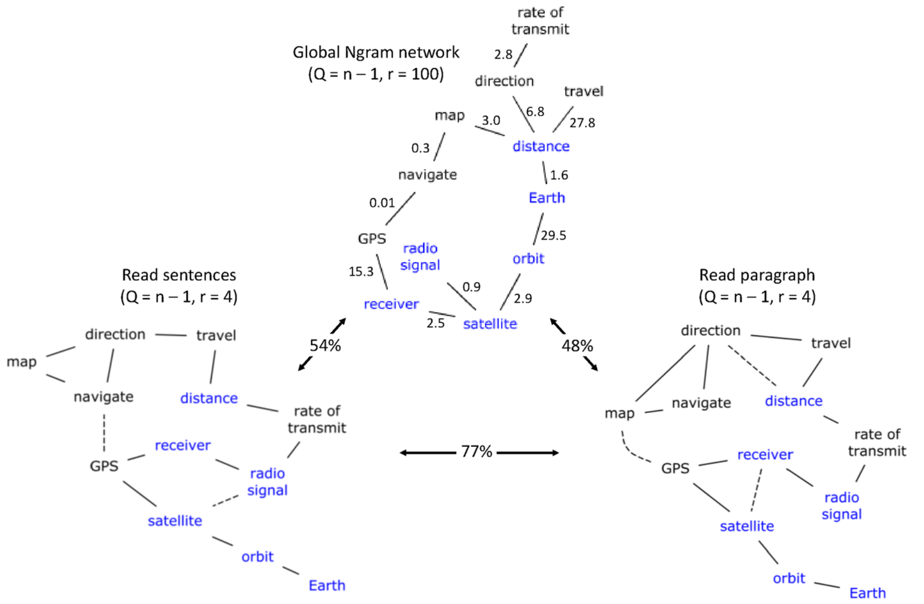

Fig. 2 The Ngram global collective knowledge network (top) and the two local collective knowledge group-average networks from Clariana et al. (2019), solid links indicate the common links in the two group-averaged networks

possible global collective knowledge structure (see: https://books.google.com/ngrams). To be specific, all pairwise combinations of the 12 terms were entered into the Google Ngram American English corpus 2008 using dependency operator and the dependency frequency weights ($\times 10^{-6}$) are shown on the Ngram network derived with Pathfinder software (see Fig. 2). Some weights are substantially greater than others, for example, the *orbit-Earth* frequency is 29.5 ($\times 10^{-6}$) while *navigating-GPS* is 0.01 ($\times 10^{-6}$) because the term Earth occurs much more often in the google corpus. The global collective knowledge Ngram network shows 54% overlap with the sentence-by-sentence group-average network and 48% overlap with the paragraph group-average network. This current investigation uses this Ngram Viewer approach to derive a global collective knowledge structure of the content in order to compare it to the local collective knowledge structure of the table and the text groups (Clariana et al., 2022).

Purpose

How does the form of a table and a parallel text passage influence posttest comprehension and post-reading knowledge structure? This experimental investigation in two studies considers the influence of reading a table versus reading a text of the same content on posttest performance and post-reading knowledge structure. KS is measured before and after reading to explore the influence of reading on KS change and to estimate the role or influence of global collective KS on these local group-level collective knowledge structures. In this study, we assumed content structures and text coherence can strongly affect reading comprehension when students lack domain knowledge. Another methodological assumption is that the aggregated collective knowledge network can partly account for individual's knowledge structure. Because the KS results are average network representations of group level cognitive structure, the findings of this investigation can offer useful insight into the group-level mental models of readers when reading a text or table.

Method

The investigation comprises two parts, an exploratory proof of concept Study 1 and a follow-up Study 2 with a larger sample size. The initial study materials proved to be adequate, so both studies use the same materials and procedures. These two studies will be described next conjointly, but then the results of each study are presented separately.

Participants

Participants were recruited from an undergraduate classroom-based hospitality management technology course in a large university (Study 1 *pool* $n = 13$ and Study 2 *pool* $n = 99$). The final participant sample sizes are for Study 1 $n = 12$, with 6 in each treatment, and for Study 2 $n = 67$ with 34 in the table and 33 in the text treatment. All participants were fluent in academic level English and were offered extra credit for participation.

Materials

All materials were presented via a Qualtrics survey as a voluntary homework assignment. The content consisted of a text on the Internet of Things (IoT) in hospitality management. Although this topic is highly related to the course, the students did not receive lectures or readings about it before participating in this research. The text consisted of 1014 words in 7 paragraphs, an introduction paragraph, five content paragraphs, and a concluding paragraph. The contents of the table were developed based on the text. The table contained 832 words, including exactly the same introduction and concluding paragraphs, plus the table portion containing the information of the five content paragraphs. The headings for each paragraph in the table and the text are: Introduction, Guest Room Automation, Mobile Engagement, Increased Personalization, Predictive/preventive Maintenance, API and 3rd Party Integration, and Drawbacks of IoT. Paragraphs 2–6 in the table and the text contain these 3 topics—definition, possible consequences of benefits, and examples.

The content knowledge pretest for the first study was composed of 10 items—two open-ended, two true/false, and six multiple-choice questions. The second study pretest consisted of eight items—one open-ended, two true/false, and five multiple-choice questions. The changes from study 1 to 2 were made to improve the pretest. The content knowledge posttest for the first study was composed of 10 items, including two open-ended, two true/false, and six multiple-choice questions. For study two, the open-ended and true/false items were converted to multiple-choice format, and one more question was added, so the posttest in the second study had 11 items, one open-ended and 10 multiple-choice questions. One question considers the main idea, seven are fact questions, and three are inference questions. Because this investigation assumes that the spatial location of the information in the text and the table are important, the location of the needed information for each posttest question in Study 2 is provided (see Fig. 3).

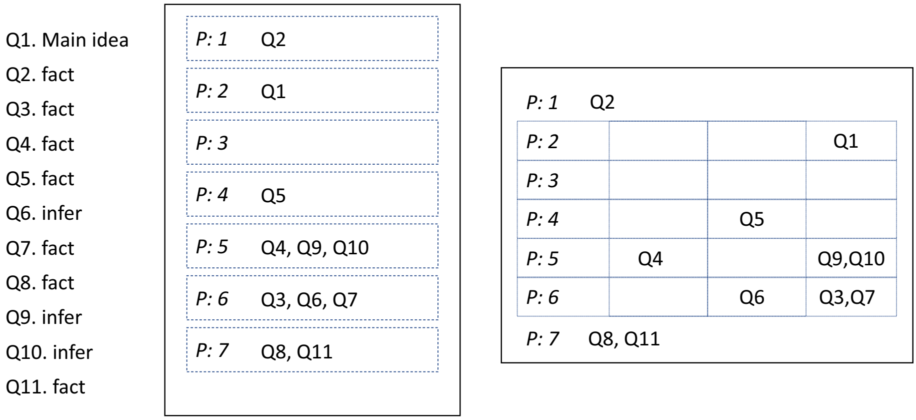

Fig. 3 The visual layout showing where the posttest items are found in the text (left) and the table (right)

A list-wise measure of KS especially suited for Qualtrics delivery was used to elicit concept association KS before and after reading (adapted from Ntshalintshali & Clariana, 2020). The KS pre and post versions were identical. This list-wise measure had 12 items, one for each key term. For each item, participants were asked to pick two words associated with that keyword (see Fig. 4). For analysis, the term-term associations for the 12 terms were entered into a 12×12 array, where 1 indicates a term-term association and 0 indicates no association. The 12×12 arrays for each participant are proximity files that were then converted to threshold networks using Pathfinder software (Schvaneveldt, 2020) and then were analyzed as percent overlap calculated as links in common between the referent and the sample divided by the average number of links in the two networks that are compared.

Procedure

In both studies, participants were randomly assigned to one of two groups, table or text. All participants were briefed on the tasks and the purpose of the investigation during the in-class time, and volunteers submitted their responses via Qualtrics. Participants at their leisure individually completed in order: (1) 12-item concept association pretest, (2) 10 (1st study) or 8 (2nd study) item content knowledge pretest, (3) Reading the text or table, (4) 12-item concept association posttest, and (5) 10 (1st study) or 11 (2nd study) item comprehension posttest. Thus, every participant within each treatments received the same materials except for their reading material. There was no time limit.

Data analysis approach

KS network of tables and text

The *ALA-reader* algorithm (Clariana, 2003) is a computer-based text analytic software tool that can convert written text directly into proximity files (prx), and then Pathfinder network software can be used to convert this prx data into network representations. This network comprises selected key concepts represented by nodes and edges between nodes

6. Application Programming Interfaces (API) are most related to: (pick two)

O Guestroom automation	O Integrating	● Security breaches
O Reducing expenses	● Connectivity	O Customer loyalty
O Mobile engagement	O Personalization	O Guest preference
O Predictive maintenance	O Internet of things (IoT)	

	API	Integrating	Security breaches	Connectivity	Customer loyalty	Etc.	Etc.
API	1	0	1	1	0	--	--
Integrating	0	1	0	0	0	--	--
Security breaches	1	0	1	0	0	--	--
Connectivity	1	0	0	1	0	--	--
Customer loyalty	0	0	0	0	1	--	--
Etc.	--	--	--	--	--	1	--
Etc.	--	--	--	--	--	--	1

Fig. 4 An example item and responses from the concept association test and a portion of the 12 × 12 proximity array showing the associations (as 1 s) for API with Security breaches and Connectivity

to demonstrate the relationship. Several investigations using *ALA Reader* have been conducted to validate and improve the method (Clariana & Wallace, 2007; Kim & Clariana, 2015, 2017; Tang & Clariana, 2017). Based on the previous empirical evidence, ALA-Reader was used to derive the conceptual structure of the table and the text.

Local collective knowledge structure as group-average KS networks

The 12 × 12 proximity files generated by individual participants (see Fig. 4) were aggregated by averaging the raw proximity files of individuals into the group average and then using the Pathfinder network tool to form the group network representations.

Global collective knowledge structure as Ngram referent network

Following the approach described by Clariana et al. (2019), a frequency-based global collective KS network of the 12 key terms was derived from the American English corpus 2008 using all pairwise term-term Google Ngram viewer dependencies frequencies (https://books.google.com/ngrams using the ≥ dependency operator). The 12 × 12 proximity array of term-term frequency values was transformed by Pathfinder software into a Threshold network using the parameter 2.0 paths (i.e., 2 times the number of terms, 2 × 12 = 24). Typically, networks are generated using the parameters Q = n – 1 and r = infinity to generate networks with the least paths necessary to connect the terms; in this case, it would result in 11 links for 12 terms (density = 11/12 = .9). However, the networks of the text and table are established from proximity arrays containing 1 s and 0 s, so these networks cannot be reduced by using any parameter and must contain all of the links (1 s), the text density was 2.3 (27 links/12 terms), and the table density was 2.6 (31 links/12 terms). For the group-average networks to be about equal in density to the table and text networks, a 2.0 threshold network parameter was used in order to establish networks with about 24 links (12 terms × 2.0 = 24).

Results

The results of the two studies are presented next. Exploratory Study 1 provides proof-of-concept, while Study 2 uses an adequate sample with random assignment to further compare and describe the data.

Study 1 Results

In exploratory study 1, the comprehension posttest data were analyzed by the one-factor analysis of variance (ANOVA). Text readers scored significantly better than table readers (M text = 6.83, SD = .98 and M table = 5.29, SD = 1.11), F (1,11) = 6.942, p = .023, ES = 1.5. Reading the text relative to reading the table also influenced the group-average post KS (i.e., network structure). For text readers, the pre-to-post KS overlap with the external representation increased from 35 to 46%, while for the table readers, the pre-to-post KS overlap with the external representation decreased from 40 to 28% (see Fig. 5). This phenomenon is an undesirable effect of reading the table. Other research has also shown that structures can degrade when it is unfamiliar to the readers (Kintsch, 1992; McNamara et al., 1996; Wright, 1980). The within-group pre-to-post group-average KS network overlap for the text was larger (67%)

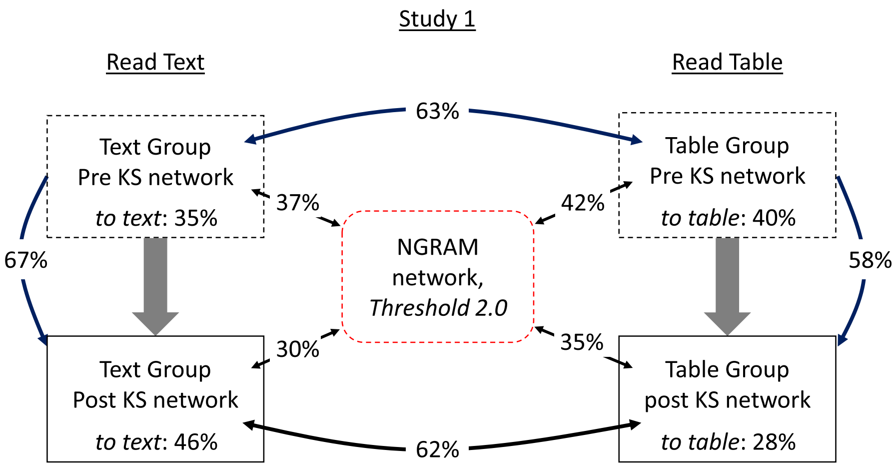

Fig. 5 The list-wise KS similarity as percent overlap of the local collective knowledge group-average networks for the text and table groups and the global collective knowledge Ngram network for Study 1

relative to the table (58%). In terms of between-group local collective knowledge structure, the two group-average networks were alike before and after reading (63% and 62% overlap) regardless of their assigned reading materials (table or text). In terms of global collective knowledge structure, the group-average networks were more like the Ngram network before reading (37% and 42% overlap) than after reading (30% and 35% overlap). This aligns with Clariana et al. (2019) that peers are more like peers, and that there is a relationship between local and global collective knowledge structures. These findings led to Study 2.

Study 2 Results

Posttest comprehension

Because the simple correlation between pretest and posttest comprehension scores is low, Pearson $r = .29$, it is not appropriate to use the comprehension pretest as a covariate (Kennedy & Bush, 1985). Comprehension pretest scores were examined to determine initial group equivalence, there was no significant difference for the Table group (n = 34, M = 4.85, SD = 1.26) versus the Text group (n = 33, M = 5.18, SD = .98), F (1,65) = 1.42, t-test p = .24.

Participants' posttest comprehension data were analyzed by ANOVA. As in Study 1, the average posttest performance for participants who read the text (M = 6.68, SD = 1.75) was significantly larger than for those who read the table (M = 5.74. SD = 2.02), F (1,65) = 4.19, $p = .04$, ES = .5. Note that these comprehension posttest means are lower than those observed in Study 1.

Mayer et al. (1983) reported that relative to a text-only (control), structured information enhanced recall of conceptual information and decreased verbatim memory (especially primacy memory of the first 10 items in the material). Thus, a possible anticipated finding for posttest comprehension was that table readers would have higher scores than text readers on the inference posttest items (e.g., conceptual) relative to fact-based items (e.g., verbatim) due to the explicit relational organization of the table. Post hoc analysis indicates that the text group was better at fact-based and main idea questions but not on the inference questions, so this finding only somewhat supports the hypothesis that tables support recall of conceptual information (see Table 1).

Local collective KS as group-average networks

Group-average KS networks allow us to note at the group level if KS is different for the text and table groups. This group-level KS analysis first looked at the similarity as percent overlap between reading text and table (Fig. 6), and the findings aligned with the comprehension test result above. For text readers, the pre-to-post KS overlap with the text referent increased from 32 to 40%, while for the table readers, the pre-to-post overlap with the table referent decreased from 31 to 25%. This group-level finding also aligns well with the Study 1 findings, however

Table 1 Comprehension posttest means for the Text and Table interventions broken out as main idea, inference, and factual items

	Main Idea	Factual	Inference	Weighted mean
Text (n = 33)	.52 (.51)	.69 (.17)	.43 (.28)	.67 (.17)
Table (n = 34)	.32 (.48)	.59 (.22)	.42 (.25)	.57 (.20)

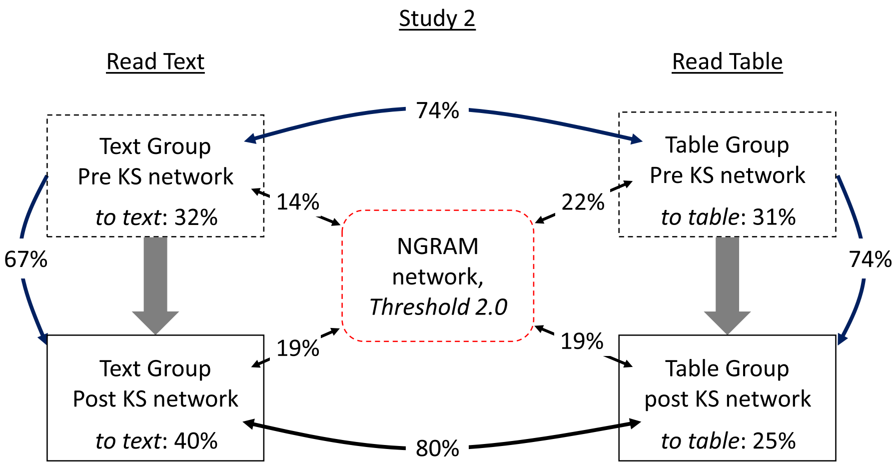

Fig. 6 The similarity as percent overlap of the local collective knowledge group-average networks (within and between groups), the combined table/text referent, and the global collective knowledge Ngram network for Study 2

the within-group pre-to-post overlap did not, in Study 2 the pre-to-post group-average network for the text group was lower (67%) relative to the table group (74%).

In terms of between-group local collective knowledge structure, the two group-average networks were very similar before and after reading (74% and 80% overlap) regardless of their reading material (text or table). In terms of global collective knowledge structure, the group-average networks were not much like the Ngram network before (14% and 22% overlap) or after reading (19% and 19% overlap). This does not align with the findings of Clariana et al. (2019) or for Study 1 above. In Study 2, peers are like peers, but the relationship between local (group-average KS) and global collective KS was no better than chance.

To better understand this, we further inspected the table and text post-group average networks and the referent network to find and compare word clusters to describe their detailed term-term associations. The Internet of Things (IoT) was both title and main idea, IoT is a central node (i.e., high degree, 7 links) in the referent network as expected. Interestingly, the text group network has IoT as a central node (5 links), but IoT was less central (4 links) in the Table group network (see Fig. 7).

This result is consistent with the posttest comprehension test result representing table readers' lower scores on the main idea. The similarity across all three networks is the term pair *predictive maintenance—reduced expenses* (this link is labeled as 1 in Fig. 6) and the four-term cluster *API—IoT—mobile engagement—personalization* (the links are labeled 2, 3, 4 in Fig. 6). The text group network had three additional links in common with the text referent, *guestroom automation—IoT—reduced expenses* and *integration—personalization* (labeled as 5, 6, and 7 in Fig. 7).

We also compared the word pairs in all networks; seven consistent word pairs occurred in all four group networks (in pre table, pre text, post table, and post text), but these seven pairs were not observed in the Ngram referent. Regarding these group-average networks, these results indicate that reading table or text did not strongly alter pre-existing word chunks, these readers show strong structural persistence of some pre-existing structure chunks.

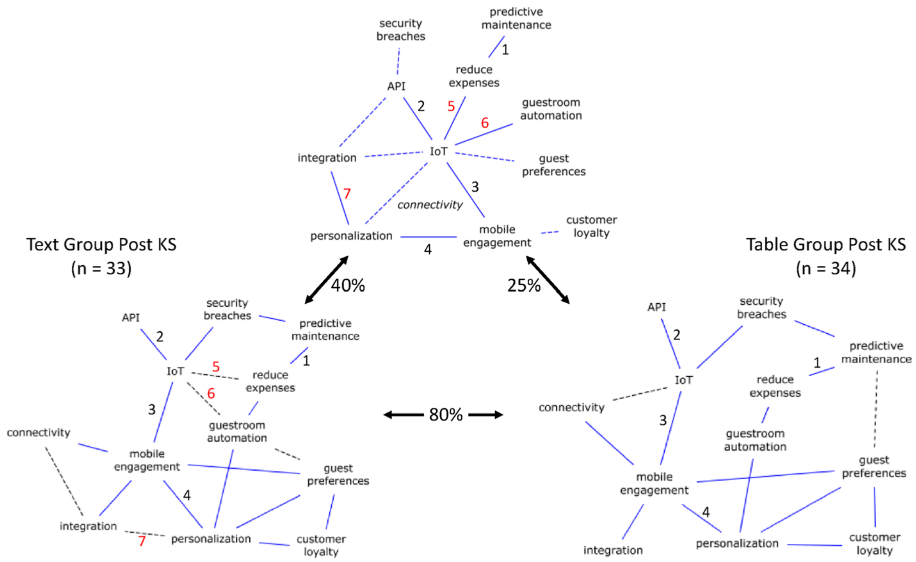

Fig. 7 Referent network (top, the averaged table, and text referents), and post group-average KS networks. Dashed links indicate unique links of the two group-averaged networks

Discussion

This investigation seeks to determine how the inherent conceptual structure of an external representation influences (1) individuals' knowledge structure relative to individual and global collective knowledge structure and (2) more fully accounts for comprehension. In two studies, knowledge structure and comprehension were measured before and after reading. The one-way ANOVA of the posttest comprehension data in both Study 1 (ES = 1.5) and Study 2 (ES = .5) showed that the text group significantly outperformed the table group ($p < .05$), mainly due to performance on factual and main idea items but not on inference items. The results demonstrate that the influence of an external representation (table and text) can be framed in terms of the representation's inherent conceptual structure, and this can be applied in future studies of the influence of external representations (Schwonke et al., 2009; Shavelson, 1972).

The descriptive comparisons of group-average pre and post KS networks in both studies showed that the two group networks were quite alike before reading and were even more alike after reading; this is peer knowledge structure convergence as local collective knowledge structure. The pre-to-post within-group network overlap was also substantial. The group-average post network for the text group from pre-to-post became more like the expert referent; in contrast, the post network for the table group from pre-to-post became less like the expert referent. In addition, the Ngram frequency network as an estimate of prior KS was supported in Study 1 but not in Study 2; this shows the potential value of a probabilistic measure of global collective knowledge to help account for pre- existing knowledge structure.

Post-reading comprehension performance reflects the network outcomes. In both Study 1 and 2, there was a marked *increase* in similarity of the Text groups' networks (Study 1: 35% increases to 46% and Study 2: 32% to 40%) however there was a marked *decrease* from pre-to-post in the KS similarity of the Table groups' networks relative to the benchmark referents (Study 1: 40% decreases to 28% and Study 2: 31% to 25%). Recall that reading comprehension of table information requires extra processes or at least less familiar processes, so one possible explanation of these results is that readers use different reading strategies when reading tables which will determine the order of how the table content is read, which then impacts comprehension (Kintsch & Yarbrough, 1982; Schnotz, 1984, 1993). Thus, the table readers likely attained a less coherent situation model of the content, so they were less able to interpret the text ideas. Said differently, this population of readers was better at reading the text than the table.

Does reading a table enable readers to be better on inference-level questions that depend on the relational closeness of the content compared to fact-based questions (Jonassen et al., 1993)? The posttest scores for main idea and fact questions of text readers exceeded table readers, but scores on the inference questions were relatively low for both groups (M = .42 and .43). Tables were not better than text for inference items in this investigation.

The large similarity of the group networks before and after reading indicates the structural persistence of pre-existing knowledge structure. Some word clusters appeared only in the group networks but not in the text, table, or the Ngram referents. We interpret this as peer-peer initial KS similarity and as durability and coherence of individuals' knowledge structure. McNamara et al. (1996) reported that readers are relatively better at reading when their background knowledge is coherent/structurally aligned with the reading. In this present investigation, the prior structural knowledge of readers was only moderately similar to the referent network (30–40% overlap), this likely leads to more difficulties in comprehension while reading. In this case, their pre-existing knowledge structures likely interfered with becoming more like the table or text that they read.

Lastly, the anticipated similarity between local and global collective KS networks remains uncertain. Although Study 1 showed a moderate relationship between the local group average networks and the global Ngram networks, this relationship was not observed in Study 2. Perhaps the Study 1 participants had more background with this content reflected as increased similarity to the global collective KS network and better comprehension pretest and posttest performance. More research is needed to determine if there is a relationship between local and global collective KS because of these mixed results.

Limitations

In regard to the generalizability, these findings that the inherent knowledge structure of external representations is an important factor that may account for the effect of the representation are limited to this specific context: the undergraduate classroom-based hospitality management technology course from the Eastern part of the US public university with the participants of relatively low prior knowledge of the content. Also, as the text and the table in this investigation were designed to have equivalent information in order to isolate the influence of the table's layout, these results should not be over-generalized to every form of table. We created this table as an external representation to compare the influence of reading a text versus table form on knowledge structure.

Also, these results are aggregate network representations of group-level cognitive structure, individuals' networks will be relatively idiosyncratic. In addition, the network results reported here depend on the keywords selected by the expert, but selecting keywords is not an exact science; using different keywords will attain slightly different results. Even so, the findings of this investigation still offer useful insight into the mental models of readers when reading a text or table.

The comprehension pretest and posttest reliability were relatively low, pretest alpha = .52 and posttest alpha = .50. We reasoned that this relatively low-reliability ties to the voluntary nature of the task (homework) and low prior knowledge of this topic. Participants completed the tasks as an extra credit assignment without any previous lectures or readings about the content. Note that test reliability relates to the sensitivity to observe a statistical difference; low reliability means more error of measurement and thus lower sensitivity. However, a significant difference between text and table on the comprehension posttest was observed suggesting that the effect is large enough in this case to overcome the limitation of the posttest reliability.

Further, students' prior experiences and the levels of interpretation in external representation were not fully considered in this research. Thus, future studies should collect a general measure of comprehension to control for this ability and should add simple instructions for how to read columns and rows in tables to minimize the influence of different ability in comprehension of table.

This Google Ngram frequency dependency network is one way to measure global collective knowledge (Clariana et al., 2022) and the list-wise measure was a new way to measure local collective knowledge. Those these new approaches produced reasonable and interpretable data, to improve methodological validity, future research should compare these to other established approaches.

Conclusion

The approaches described here for rendering text and table artifacts as networks and for determining group level local collective knowledge and global collective knowledge networks directly inform two factors of the Cognitive principles of Message Design Theory that include facilitating attention, facilitating perception, facilitating processing, and facilitating memory (Pettersson, 2012). These network approaches allow objective comparisons of readers' knowledge structure (a measure of cognition) with the domain knowledge conceptual structure to compare message redundancy in the artifacts, which may be an important message design issue (Corradi et al., 2014).

The critical point we make in this investigation is that the conceptual structure of the learning artifacts is a central aspect of the influence and effect of the artifacts. Knowledge structure tools such as *ALA-Reader*, *GIKS* (Kim, 2019), *DEEP* (Spector & Koszalka, 2004), and *HIMATT* (Pirnay-Dummer et al., 2010) that create concept association networks of text and other information sources will expand the explanatory power of future research with Multiple External Representations (MERs) and with message design.

In summary, reading the text was clearly better than reading the table for these students for both comprehension and knowledge structure outcomes. These findings indicate that practitioners should be careful when using tables as an instructional resource because reading tables, charts, and graphs is an essential skill, and students need explicit training on how to use these in the classroom (Shreiner & Dykes, 2021).

Declarations

Conflict of interest The authors declare that we have no potential conflicts of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. This article does not contain any studies involving animals performed by any of the authors.

Informed consent Implied or verbal consent was obtained. Subjects did not sign a consent form (waiver of written documentation of consent). The research presents no more that minimal risk of harm to subjects and involves no procedures for which written consent is normally required outside of the research context.

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