Summary Writing as a Process of Building a Solid Mental Model: A Global Index to Describe Knowledge Structure Change

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Abstract: Summaries serve as a means of evaluating the latent knowledge structure of students' reading comprehension. A previous study revealed the need to further know about how students develop the structure of mental models toward a better understanding of the complex reading. This case study explored the global index, Graph Centrality, as a measure to describe and detect a student mental model, in particular, its structure, and also its relation to the quality of understanding. The results of this initial investigation are promising, demonstrating that the potential of the index to describe students' revision behaviors, the patterns of knowledge structure change, the degree of mental model modification that connects to the quality of understanding. This study paves the way for further investigation of the role of the index with large sample size.

Introduction

Summary writing is a common classroom learning strategy (Singer & Alexander, 2017; Stevens, Park, & Vaughn, 2019). Summarizing "requires readers to sift through large units of text, differentiate important from unimportant ideas, and then synthesize those ideas and create a new coherent text" (Dole et al., p. 244, as cited in Duke & Pearson, 2009). A quality summary requires a deep comprehension of the text (Westby, Culatta, Lawrence, & Hall-Kenyon, 2010). Thus, summaries can serve as a powerful lens through which to assess learners' comprehension. Further, helping students to write higher quality summaries can help students to improve their comprehension.

The Student Mental Model Analyzer for Research and Teaching (SMART; Kim, Gaul, Kim, & Madathany, 2019) is an automated system that leverages natural language processing to assess the nature of students' summaries with attention to key concepts and relations in a text. In SMART, students read informational texts (articles, book chapters) and write summaries of what they read. SMART analyzes the quality of a student summary by eliciting its underlying mental model in the form of a concept map, utilizing multi-dimensional (surface, structure, semantic) indices and computing similarities that assess the extent to which a student's model is close to a reference model (expert model). A previous study showed that students built on SMART feedback to write more expert-like summaries (Kim et al., 2019). Despite the prominent findings, structure-related indices on SMART appeared inconsistent in patterns, which called for further investigation on mental model change in the structure.

The current study uses a case study approach to explore the potential of a global index that can characterize a holistic structure of mental representation, indicates the degree of change in the mental model structures, and relates to the quality of the mental model in terms of appropriate connections of key ideas from the text. We expect that this study can put a cornerstone to guide and elaborate future studies that examine the central assumption that learning progression in summary writing is a set of directional changes in a learner's mental representations of the text.

Theoretical foundations

This line of work is grounded in theories of mental models and discourse comprehension (Graesser, Singer, & Trabasso, 1994). These theories posit that comprehension emerges from the construction of a coherent *mental model,* or mental representation. These mental models are multidimensional and include information that is explicit in the text as well as extratextual information that helps to connect ideas from across disparate parts of the text as well as to information in prior knowledge (Graesser, Singer, & Trabasso, 1994).

One limitation in this area of work has been that researchers often explore a student's mental model as a static "outcome". In reality, learning from text is a process in which the concepts and relations included in the mental model are gradually modified or abruptly shift to a new model through instruction in the direction of an expert-like knowledge structure (Graesser et al., 1994). Students write their initial summary, activating relevant prior knowledge to understand a new text (Bransford & Schwartz, 1999; Gentner, Holyoak, & Kokinov, 2001). For example, some students write a verbose summary, but include unnecessary concepts from their prior knowledge or too many details instead of main ideas. In contrast, some students focus on a preferred main idea that attends to their beliefs and existing mental model, while ignoring other critical, but belief-inconsistent main ideas. Both models are not enough to properly cover the main ideas of the text. Given the feedback information about their summary, students rethink and revise their summary, which stems from their mental model modification.

Progress in mental models involves both quantitative and qualitative change (Kim, 2015; Kim et al., 2018; Siegler et al., 2009). For example, students enlarge their mental models by adding new concepts from the text or optimize their models by dropping less important concepts. Accommodation to new inferences by the addition and reduction approaches involves the modification of an entire model structure (Norman, 1983; Rumelhart & Norman, 1978). Thus, much can be gleaned from evaluating the change in a reader's mental model structure (Kim et al., 2018). However, the current assessment methods have not yet given enough accounts of how mental models change as a learning outcome (Kim, Zouaq, & Kim, 2016; Westby et al., 2010).

Learning progress in summary writing can be explained as a series of gradual or radical changes in mental model states that can be facilitated by instruction and feedback (Kim, 2015; Siegler, Thompson, & Opfer, 2009).

Assessing latent structure of a mental model

Advances in natural language processing techniques over the past few decades have allowed researchers to use students' open-ended responses to assess the latent structure of a students' mental model (Jain, Kulkarni, & Shah, 2018). That is, NLP allows researchers to quantify the words, ideas, and connections between ideas in a student summary to "see" the structure of the student's mental model. SMART does this by producing concept maps of the ideas and connections in student summaries.

Concept map morphology studies suggest that learners 'switch,' 'change,' 'link' between two different types of structure: chain (linear) and net (network) structure (Kinchin, 2008). Mental models are characterized as having a chain shape when a student writes evenly distributed concepts, centering on a key concept. A thoughtful chain structure is indicative of a goal-directed mental representation at a micro-level structure (Hay & Kinchin, 2006; van Dijk & Kintsch, 1983).

Some concepts are overlapped across subgroups (chains) and connect the subgroups together. Key concepts linking more subgroups tend to further stand toward the center of the network (Kim et al., 2019). Chain structures connected by bridging concepts form an integrated and holistic net structure together, which is called a cohesive macrostructure (Kintsch, 1998). On the other hand, a net structure composed of ill-defined chains reflects a naïve epistemology, connecting many concepts that are not grouped in chunks of proper propositional relations (chains; Hay & Kinchin, 2006). A dynamic transformation of knowledge structure, involving chains and nets, warrants a better way to detect, describe, and interpret the structure of the mental model. We provide more detail in the calculation of these indices in the method.

3S indices

As described previously, mental models are multi-faceted. The current study uses the 3S model of knowledge structures. 3S characterizes three dimensions of a knowledge structure: (a) surface, (b) structure, and (c) semantic (Kim, 2015; Ifenthaler, 2014). The surface dimension indicates the descriptive information of components of mental representation (e.g., number of concepts, Surge, 1995). The structural dimension represents the holistic characteristics of the mental model, such as size, cohesiveness, and complexity (Gentner et al., 2001). The semantic dimension relates to the underlying ideas in the text, more specifically, individual concepts and propositional relations in a model (Kintsch & van Dijk, 1978).

Previous studies (Kim, 2015) demonstrated that the three dimensions explain different aspects of mental models. Building on the three-dimensional framework and the previous findings, we developed SMART analytics that measures multiple indices of the three dimensions. An empirical study (Gaul, Bundrage, Madathany, & Kim, 2020) showed that the surface and semantic dimensions tended to change in a similar direction, while the indices of the structural dimension appeared to exhibit different patterns within and across dimensions. Although the findings of the study supported the theories that explain deep comprehension emerges from constructing an interconnected mental model (Kintsch, 1998), structure-related indices demonstrated inconsistent patterns among students, which left the structural changes of mental models and their relationships with obtaining a better understanding of the text unexplained.

Graph centrality

One means of disentangling the shifts in these dimensions may be to explore a more holistic evaluation of the student's mental model that considers these three dimensions in tandem. Degree centrality is an index that describes the number of relations connected to a concept in a concept map (Newman, 2010). For example, the concept ("learning") can be connected to "process" and "performance" in a sentence of the summary ("Some say learning is a process of change, and some define learning as an individual's performance."). Then, the degree centrality of the concept ("learning") is two.

In this study, we used the degree centrality of a whole concept map, which is called 'Graph Centrality (GC).' As its name indicates, GC is a measure of a whole map by extending individual concepts' degree centrality values into the entire network level (Clariana, Draper, & Land, 2011). A GC value can indicate distinct characteristics of a holistic structure of a mental model.

The current study

The current study uses data from an online course to examine how students' summaries and summary revisions can be used to better understand students' learning process. In particular, we explored how *graph centrality* of the students' summaries revealed learning progression in reading comprehension. We leveraged a descriptive case study approach to examine the potential value of a global index, graph centrality, in understanding the structural change of students' mental models. We inspected these summaries and revisions for (a) overall shifts in the global index as indicative of knowledge structure change, (b) the relationships of the global index with the indices from the three dimensions. In addition, we conducted visual inspections of selected students' mental representations that were rendered through a Social Network Analysis application (NodeXL; Hansen, Shneiderman, & Smith, 2011).

We hypothesized that a well-structured mental model could combine many linear structures (chains) to a connected net shape of a concept map, which resulted in a GC index value closer to the goal-orientation threshold value of 1. In this regard, we computed GC values for student models and an expert model, tracked the overall shifts in the values, and compared GC values to the 3S indices and similarity measures from the SMART tool. In addition, we conducted visual inspections of the expert model and selected students' mental representations.

Method

Context and participants

These data come from a larger design implementation study conducted with 38 students who enrolled in across two semesters of a graduate-level asynchronous online course. Each week, students completed weekly readings, submitted a reading summary, took a quiz, and participated in a student-led online discussion. Students were instructed to write 250-300 words summaries that thoroughly covered the key concepts of the reading. On weeks four, seven, and eleven, students submitted their summaries to SMART, where they were encouraged to make multiple revisions to their summaries based on the feedback that SMART provides.

The current case study focuses on one of the readings from week 4. This text was about constructivist instructional approaches and was 10 pages long (~7,000 words). This activity was selected because the highest number of students (n = 14) submitted multiple summary revisions (more than one revision). Data preview revealed that four students made multiple submissions with no edits in their summaries. These four students were omitted, leaving 10 cases for this exploratory analysis.

3S indices and similarity measures

The analyses of student mental models are dependent upon the measurement traits and context. In this current study, students write summaries of the text they have read in SMART. Building on Montague's (1974) formal semantics that emphasizes the role of syntax to determine the meaning of a complex text, SMART uses a state-of-the-art Natural Language Processing (NLP) package to extract concepts from the text in the forms of single nouns (e.g., comprehension) or compounding nouns (e.g., "learning sciences" as a noun + noun compound).

The relations between pairs of concepts are determined based on the adjacent relation (AR) principle that regards two concepts next to each other as related to the assumption that closely related concepts tend to be closer to each other (Clariana, 2010). The adjacent relation approach is regarded as beneficial for two reasons: (a) the method allows all concepts identified from a text to be included in a richly connected concept map (i.e., open-ended approach) and (b) above all, AR is the easiest way to determine concept relations in a text.

An array of concept-to-concept relations forms a concept map as a re-represented student mental model of facts, concepts, and symbols (Kim et al., 2016,; Kim et al., 2018). Leveraging network analysis methods (Coronges, Stacy, & Valente, 2007), SMART compute multiple concept map indices, each of which corresponds to one of the 3S dimensions (see Table 1).

These indices can describe the characteristics of a student model in the three dimensions. Also, we can evaluate the quality of a student summary by examining how a student model is close to a reference model (i.e., an expert model that is generated from an expert's exemplary summary). This evaluation can be done by comparing student indices to corresponding indices from a reference model. Accordingly, a similarity measure per index ranges 0 (completely dissimilar) to 1 (completely dissimilar). Kim et al. (2019) proposed two types of similarity formulas: numerical and conceptual similarity. The numerical similarity formula that compares two numerical measures is applied for all the 3S indices.

$$s = 1 - \frac{|v_1 - v_2|}{max\ (v, v_2)}$$

where $v1$ is the value of a student model, and $v2$ is the value of a reference model. In contrast, the conceptual similarity was used for the two similarity measures, such as concept matching and propositional matching, that indicate the extent to which the paired models share the same elements.

Table 1: 3S indices and similarity measures

Similarity Measure	Definition	Indices Compared	
		Operationalization	3S structure
Number of concepts*	Compare the number of concepts (nodes) in two models	The overall number of concepts	Surface
Number of relations*	Compare the number of links (edges) in two models	The overall number of relations of paired concepts	Surface
Density of graphs*	Compare the density of the two models	The density of a concept map indicates how cohesive it is.	Surface
Average Degree*	Compare the average number of degrees in two models	As the number of incoming and outgoing relations grows, the complexity of the cognitive structure is considered higher.	Structure
Mean Distance*	Compare the mean distances in two models	Indicates how close the concepts are to one another.	Structure
Diameter *	Compare the largest geodesics in two models	Represents how broad the understanding of a domain is	Structure
Concept Matching	Compare semantically identical concepts, including contextual and principle variables	Qualitative comparison	Semantic
Propositional Matching	Compare fully identical propositions (edges) between two concept maps	Qualitative comparison	Semantic
Recall-C	The proportion of key concepts that appear in a student summary	The number of key concepts	Semantic
Recall-P	The proportion of key relations that appear in a student summary	The number of key relations	Semantic

Note. * Indices available in SMART. The table was modified from Kim (2015, p.8).

The conceptual similarity formula computes the extent to which concepts and relations of concepts used in a student model are overlapped with those in a reference model. The conceptual similarity is used for concept matching and propositional matching. The conceptual similarity draws on Tversky's (1977) similarity formula:

$$s = \frac{f(A \cap B)}{f(A \cap B) + \alpha \cdot f(A - B) + \beta \cdot f(B - A)}$$

where 'A' is a student model, and 'B' is a reference model. The weighting functions, α and β, were set as 0.7 and 0.3, according to the suggestion that α should be weighted higher than β in an asymmetric relation wherein a student model resembles a reference model (Kim, 2015).

In addition to these similarity measures, the current study added two similarity measures, Recall-C and Recall-P measures, that are provided by the SMART system. The Recall-C measure indicates the proportion of fully identical key concepts (i.e., the writer's central ideas), while the Recall-P measure indicates the extent of the overlapping of the relations of key concepts identified in both student and reference model. These structure-related indices and similarity measures relate to multi-faceted mental model structure, generally showing divergent patterns while students made summary revisions (Kim et al., 2019; Kim et al., 2018). Such diversity in patterns makes it difficult to interpret how students developed mental models of the text. In this study, we viewed that the multidimensional indices and similarity measures could supplement the explanation of student mental model change in combination with the global index.

Graph centrality

In this study, we used the degree centrality of a whole concept map, which is called 'Graph Centrality (GC).' As its name indicates, GC is a measure of a whole map by extending individual concepts' degree centrality values into the entire network level (Clariana, Draper, & Land, 2011). A value of GC is calculated as follows:

- Equation 1, Degree centrality of a concept: $DC(v) = degree(v)/(n-1)$
- Equation 2, Degree centrality of a graph: $DC(G) = \Sigma(i = 1 \text{ to } v)\ [DC(v^*) - DC(vi)]/(n-2)$

where v is a concept in a network graph, n indicates the total number of concepts in a network graph, $DC(v^*)$ indicates the highest degree centrality of a concept, and $DC(vi)$ is the degree centrality of the i^{th} concept. GC yields a value between 0 to 1.

A GC value can indicate distinct characteristics of a holistic structure of a mental model. For example, a chain/linear structure forms an evenly distributed connection among concepts, likely indicating the competence of involved concepts. In contrast, a net shape represents complex and dynamic interactions among concepts from the subgroups (chains), explaining the understanding of the connected linear structures. Accordingly, both linear and network structures together build a whole knowledge structure (Hay & Kinchin, 2006; Yin, Vanides, Ruiz-Primo, Ayala, & Shavelson, 2005). Scholars suggested two distinct characteristics of a holistic structure: one end is the goal-orientation focusing on internalizing exact concepts and propositions that students should learn from the text (i.e., $DC(G)$ below 0.1), while the other end is towards the naïve epistemology that indicates the lack of understanding of the text (i.e., $DC(G)$ greater than 0.6) (Hay & Kinchin, 2006; Yin et al., 2005).

Results and discussion

GC trends

We examined GC values of the initial and the final summaries of each case (Table 2). We noted that there was not uniform change in GC values. We classified changes in one of four trends: positive, low negative (below the 25th percentile), medium negative (25th - 75th percentile), and high negative (over the 75th percentile).

Table 2: Trends of graph centrality change

Student	Initial GC	Final GC	GC Change	Trend
S10	0.110	0.119	0.009	Positive
S16	0.117	0.148	0.031	Positive
S2	0.153	0.149	-0.004	Low Negative
S22	0.124	0.113	-0.011	Low Negative
S5	0.075	0.056	-0.019	Medium Negative
S8	0.094	0.081	-0.013	Medium Negative
S19	0.25	0.206	-0.044	Medium Negative
S21	0.151	0.107	-0.044	Medium Negative
S11	0.230	0.105	-0.125	High Negative
S17	0.160	0.067	-0.093	High Negative

Model modification patterns

We assumed the different GC trends could explain students' summary revision behaviors, structural changes in mental models, and the quality of the summary. The differences in the overall changes of the mental models across the four trends can be described by a combination of the 3S indices and similarity measures (see Table 3).

Student models with positive change in GC values tended to start with a larger corpus of words in summaries and reduced words through revisions (deletion). Conversely, summary revisions with decreasing GC values had begun with a relatively small number of words and enlarged words throughout revisions (addition). The former resulted in an increase in the Density and Mean Distance but remained at a similar network size (i.e., Diameter). The latter showed a reverse pattern, decreasing Density and Mean Distance and increasing Diameter. Intriguingly, the two ends of the trend continuum (i.e., positive and high negative groups) demonstrated a greater increase in the semantic indices. Either strong deletion or addition behaviors in summary revisions enabled more proper concepts and propositional relations to reside in the final mental models.

The results of this case study indicated the potential of GC as a global index to track the degree of the structural change of mental models that could explain the extent of the improvement in the quality of the models. We transformed these indices as well as similarity values into standardized scores and computed standardized mean scores to show distinct differences among the GC trends (Flunger et al., 2017). As Figure 1 depicts, the 3S indices of the four GC trends differed notably. Also, across all similarity measures, the high negative GC group (L3) demonstrated the highest similarity values, which meant those students constructed a mental model more similar to a reference model than other groups.

Visual inspections

To further examine, we conducted qualitative analyses for three cases: the reference model (expert model), student 16 (who demonstrated higher positive change in GC values), and student 17 (who uniquely showed great negative changes in GC values).

Table 3: 3S indices by GC trends

GC Trend	ID	Attempt	GC	3S Indices								
				NW	**NC**	**NR**	**NKC**	**NKR**	**DE**	**AD**	**MD**	**DIA**
Positive	S10	Initial	**0.110**	259	73	85	3	2	0.032	2.329	4.774	16
		Final	**0.119**	296	84	98	10	30	0.028	2.333	4.774	16
		Change	**0.009**	37	11	13	7	28	-0.004	0.004	0.000	0.000
	S16	Initial	**0.117**	528	89	138	4	4	0.033	2.899	4.047	10
		Final	**0.148**	365	65	96	5	7	0.044	2.769	4.128	10
		Change	**0.031**	-163	-24	-42	1	3	0.011	-0.13	0.081	0
	Average (F-1)		**0.020**	-63.0	-6.5	-14.5	4.0	15.5	0.004	-0.063	0.041	0.000
Low Negative	S2	Initial	**0.153**	243	52	68	2	0	0.049	2.5	3.741	10
		Final	**0.149**	250	53	70	2	0	0.049	2.528	3.587	9
		Change	**-0.004**	7	1	2	0	0	0	0.028	-0.154	-1
	S22	Initial	**0.124**	222	57	66	3	2	0.041	2.281	4.622	14
		Final	**0.113**	319	80	93	9	28	0.029	2.3	4.222	19
		Change	**-0.011**	97	23	27	6	26	-0.012	0.019	-0.4	5
	Average (F-1)		**-0.008**	52.0	12.0	14.5	3.0	13.0	-0.006	0.023	-0.277	2.000
Mid Negative	S5	Initial	**0.075**	205	54	58	2	0	0.041	2.148	8.966	28
		Final	**0.056**	260	71	77	8	16	0.031	2.169	4.946	24
		Change	**-0.019**	55	17	19	6	16	-0.01	0.021	-4.02	-4
	S8	Initial	**0.094**	234	51	65	2	1	0.049	2.471	3.169	12
		Final	**0.081**	434	96	118	1	0	0.026	2.438	4.952	19
		Change	**-0.013**	200	45	53	-1	-1	-0.023	-0.033	1.783	7
	S19	Initial	**0.250**	245	44	61	4	5	0.063	2.705	3.396	8
		Final	**0.206**	229	43	60	8	16	0.065	2.744	3.282	8
		Change	**-0.044**	-16	-1	-1	4	11	0.002	0.039	-0.114	0
	S21	Initial	**0.151**	353	87	100	3	2	0.026	2.276	5.393	15
		Final	**0.107**	416	102	124	9	23	0.023	2.373	4.644	24
		Change	**-0.044**	63	15	24	6	21	-0.003	0.097	-0.749	9
	Average (F-1)		**-0.030**	75.5	19.0	23.8	3.8	11.8	-0.009	0.031	-0.775	3.000
High Negative	S11	Initial	**0.230**	256	57	75	4	0	0.046	2.544	3.575	12
		Final	**0.105**	246	58	65	4	0	0.039	2.241	3.777	13
		Change	**-0.125**	-10	1	-10	0	0	-0.007	-0.303	0.202	1
	S17	Initial	**0.160**	231	56	75	5	7	0.045	2.5	4.54	11
		Final	**0.067**	272	69	93	10	30	0.038	2.565	4.298	14
		Change	**-0.093**	41	13	18	5	23	-0.007	0.065	-0.242	3
	Average (F-1)		**-0.109**	15.5	7.0	4.0	2.5	11.5	-0.007	-0.119	-0.020	2.000
EXPERT MODEL			**0.056**	241	82	67	10	30	0.036	2.373	4.315	13

Note. Graph Centrality (GC), Number of Words (NW), Number of Concepts (NC), Number of Relations (NR), Number of Key Concepts (NKC), Number of Key Relations (NRC), Average Degree (AD), Density (DE), Mean Distance (MD), Diameter (DIA)

As Figure 1 shows, the expert concept map forms a cohesive macrostructure in which many key concepts (the squares) weaved sub-chain structures together (Kintsch, 1998). The local structures of the summary (i.e., a sentence or a paragraph) appear linear and goal-directed (Hay & Kinchin, 2006; van Dijk & Kintsch, 1983). In contrast, Student 16's final summary creates a net structure with few sub-chains, indicative of naïve epistemology (Hay & Kinchin, 2006). Although this model embeds several key concepts, the key concepts do not serve as cohesion cues (van Dijk & Kintsch, 1983) mapping local and distal constituents in the text (i.e., relationships between linear subgroups–sentences). While the student reduces the size of the model, the key concepts are located off to the side of the model. In contrast, the final model of student 17 demonstrates a goal-directed structure with most key concepts mapping sub-chain components similar to the expert model. This case shows that the higher degree of negative GC change in a model indicates the addition approach to summary revisions and perhaps relates to the mental model change toward a proper knowledge structure of the text.

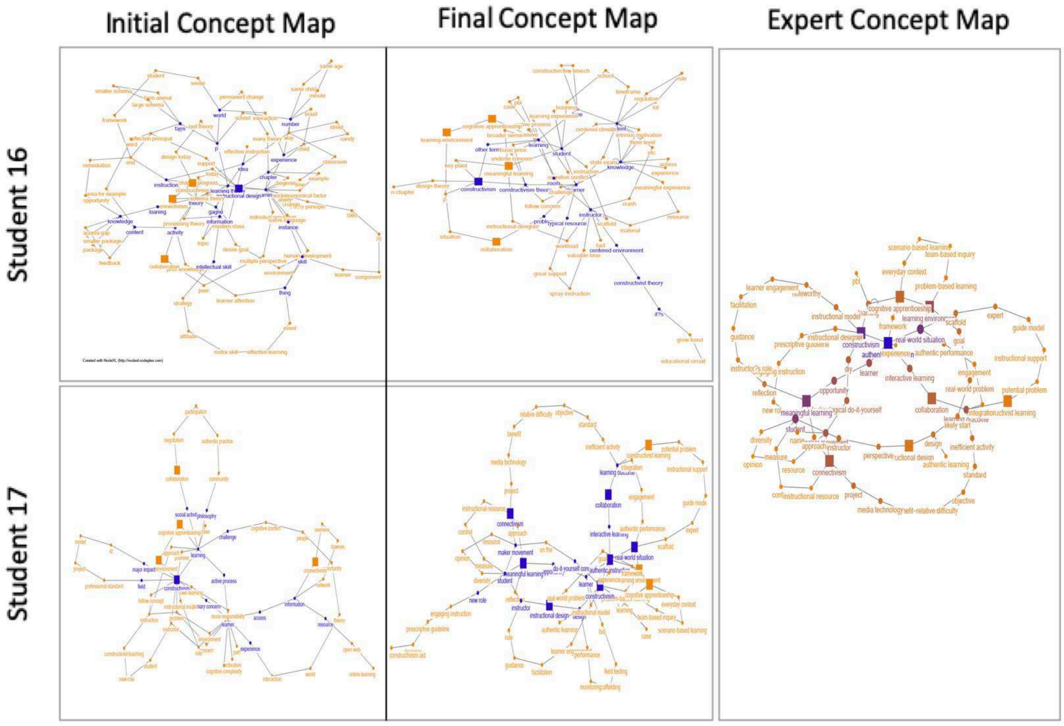

Figure 1. Graphical representations of the knowledge structures.

Conclusion

The present case study explored the use of Graph Centrality (GC) as a global index of students' mental model quality and, in particular, students' mental model *change* as they wrote and revised summaries in SMART. Analyses revealed that GC change (i.e., negative vs. positive change) related to how the students modified the wholistic structure of their mental models (e.g., addition vs. deletion approach). A higher degree of GC change appeared to indicate an appropriate reconstruction of the knowledge structure toward an expert-like understanding of the text, using more key concepts from the text and producing more cohesive sub-chain structures. The graph centrality index may serve as a way to better characterize these important qualitative shifts in mental model structure that may not be immediately apparent in the 3S indices.

Methodologically, this study suggests that the GC index could be beneficial to describe the overall change of a student mental model along with the 3S indices (e.g., surface, structure, semantic). Pedagogically, the GC index available in a formative assessment and feedback technology like SMART could track the overall mental model trajectories in real-time and inform students of the quality of their understanding of the text and help instructors to deliver targeted feedback and support.

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