Computational narrative mapping for the acquisition and representation of lessons learned knowledge

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Abstract

Lessons learned knowledge is traditionally gained from trial and error or narratives describing past experiences. Learning from narratives is the preferred option to transfer lessons learned knowledge. However, learners with insufficient prior knowledge often experience difficulties in grasping the right information from narratives. This paper introduces an approach that uses narrative maps to represent lessons learned knowledge to help learners understand narratives. Since narrative mapping is a time-consuming, labor-intensive and knowledge-intensive process, the proposed approach is supported by a computational narrative mapping (CNM) method to automate the process. CNM incorporates advanced technologies, such as computational linguistics and artificial intelligence (AI), to identify and extract critical narrative elements from an unstructured, text-based narrative and organize them into a structured narrative map representation. This research uses a case study conducted in the construction industry to evaluate CNM performance in comparison with existing paragraph and concept mapping approaches. Among the results, over 90% of respondents asserted that CNM enhanced their understanding of the lessons learned. CNM's performance in identifying and extracting narrative elements was evaluated through an experiment using real-life narratives from a reminiscence study. The experiment recorded a precision and recall rate of over 75%.

Highlights

- Learning from narratives of past experiences is vital to transfer lessons learned knowledge.

- Narrative maps are used to represent lessons learned knowledge.
- Computational narrative mapping (CNM) is used to automate the narrative mapping process.
- A prototype of CNM was built and trial implemented in the construction industry.
- The results show that CNM performs significantly better than existing approaches.

Keywords
Knowledge management; Lessons learned; Knowledge acquisition; Knowledge representation; Human learning; Computational narrative mapping

1. Introduction

Organizations must confront a range of uncertainties and challenges as the world becomes more complex and chaotic. As a result, companies have started to prepare themselves for these changes (Geissle and Krys, 2013). Decision-making, which mainly relies on human knowledge and experiences, is listed as one of the top 10 organizational challenges (McKinsey Quarterly, 2007). Lessons learned is a prevalent learning method for both individuals and organizations. According to the Center for Army Lessons Learned (CALL) of the United States Army Combined Arms Center (2009), lessons learned is defined as approved knowledge and experiences that induce individuals to reflect on their actions.

The National Aeronautics and Space Administration (NASA) expresses the view that the lessons learned can trigger a significant positive response, reinforcing the good aspects and experiences gained from previous lessons (2002). Weber et al. (2001) supported the idea that positive improvement will occur after the lessons learned process. Lessons learned indeed make use of organizational memory or experience to foster understanding and learning. Through hands-on practice, original thoughts or mental models have been deeply changed. Traditionally, people gain lessons learned in two ways: trial and error and learning from past experiences. The first approach mainly depends on the learners' capability, while the second approach relies on the knowledge shared by experts or knowledge workers. In the first approach, individuals may have to first suffer severe consequences through trial and error, such as financial loss or injuries, before learning occurs. This is usually not the case in the second approach.

Executives have started to face challenges induced by the retirement of the baby boomers (Rupčić, 2017; American Productivity and Quality Center [APQC], 2008; Toossi, 2004). Since most organizations conducted a massive recruitment of baby

boomers during the 1970s and 1980s, a retirement tsunami began in in 2015 (Angeloni and Borgonovi, 2016). This trend is expected to last for 10 to 15 years (Joe et al., 2013). Around 21 percent of the U.S. working population, are retired in 2014. It is expected to increase to 24.8% by 2024 (Toossi, 2015). This situation is prevalent in other developed countries as well. As large numbers of highly skilled and experienced employees leave their workplaces, opportunities for learning from past experiences are fast diminishing (Sumbal et al., 2017). The critical knowledge and invaluable experience of skilled employees will soon disappear, and opportunities to gain lessons learned from past experiences will be limited. Since knowledge gained from past experiences and lessons learned in organizations is an invaluable asset for enterprises (Bonjour et al., 2014; Sharma and Bhattacharya, 2013), there is an urgent need to retain this knowledge and help employees acquire lessons learned from past experiences.

Narratives exist in the human world in an infinite diversity of forms. Researchers agree that the real-world narratives shared by experts and knowledge workers are helpful in educating novices to learn new knowledge and skills (Lawrence and Paige, 2016; Burke and Kass 1995). A narrative helps to retain human memory, especially cultural memories of the past. Apart from retaining knowledge and wisdom, narratives are useful tools for humans to recall and share knowledge during their lifespans (Burnett et al., 2015; Bluck and Glück, 2004). A narrative is an important means to represent and transfer lessons learned to novices (Lawrence and Paige, 2016; Tappan and Brown, 1989). Geiger and Schreyögg (2012) argue that narratives aid in knowledge retention, sharing and problem solving. However, the narratives that store invaluable knowledge and experience are often embedded in the minds of knowledge workers or organizational documents, such as reviews, reports and guidebooks (Štajner and Mladenić, 2009; Spender, 1996). Traditionally, knowledge workers need to work with their mentors for a certain period or review previous organizational documents to gain lessons learned about the organization (Maruta, 2014). This process can be lengthy, and moreover, workers may not gain the correct lessons learned when they review organizational documents.

Studies have shown that using a narrative map can improve reading comprehension among skilled readers, less skilled readers and readers with learning disabilities (Derefinko et al., 2014; Idol, 1987). A narrative map is regarded as an effective tool to help learners understand narratives (Stringfield et al., 2011; Burke, 2004). Therefore, this study attempts to investigate human learning processes for lessons learned in order to develop an approach to foster quality learning from narrative texts. In addition, it proposes a systematic narrative mapping method to construct narrative maps for

acquiring and representing lessons learned knowledge. Since manual narrative mapping is inconsistent, time-consuming, labor-intensive and knowledge-intensive, this paper aims to develop a computational method to automatically conduct narrative mapping and generate narrative maps.

This paper makes the following contributions: 1) A narrative mapping method is developed to represent lessons learned knowledge and help learners better understand narratives of past experiences; and 2) A computational narrative mapping (CNM) method is developed to automate the proposed narrative mapping and facilitate the narrative map construction process. Two algorithms in CNM have been designed and developed to automatically convert narrative texts into narrative maps. The resulting narrative maps have a simple and concise structure that can facilitate lessons learned. A case study and an experiment-based evaluation are conducted to measure the performance of the proposed solution.

The rest of the paper is structured as follows. The relevant literature is analyzed in Section 2. The proposed methodology is introduced in Section 3. Section 4 describes the evaluation methods, including a case study and an experiment, while Section 5 discusses the results of the evaluations. Section 6 concludes the paper and provides ideas for future work.

2. Relevant literature

This section reviews research on human learning using lessons learned and narratives, as well as current approaches for constructing lessons learned systems and narrative databases. Narrative mapping and other computational approaches are discussed to aid in the design and development of a novel narrative mapping method for the acquisition and representation of lessons learned knowledge.

2.1 Human learning related to lessons learned and texts

Experience plays an important role in the learning process in the experiential learning model (Phelps, et al., 2016; Coffield et al., 2004; Kolb, 1984), demonstrating a significant correlation with the trial-and-error approach of lessons learned. In the view of Kolb (1984), experiential learning is defined as a process to group and understand experience, and then transform this experience to knowledge. It is similar in nature to lessons learned, as both emphasize that knowledge is gained through experience (Coffield et al., 2004; Kolb, 1984). However, individuals may repeat certain mistakes

and suffer severe consequences when they misunderstand or neglect the lessons learned.

Researchers have advocated the use of real-world narratives shared by experts and knowledge workers to help in educating novices to learn new knowledge and skills (Lawrence and Paige, 2016; Burke and Kass 1995). Through reading texts, humans can construct coherent situations models related to the texts. Coherent situations models are regarded as the mental representation of a text after readers have associated it with their previous knowledge and experience (Kirby and Lawson, 2012). However, different people can interpret the same text in different ways. One of the challenges is the reader's competence in understanding the text. If readers have difficulties understanding the text, they may not derive the correct messages from it. If the human brain mainly focuses on understanding the texts, they allocate less processing power and storage capacity to making inferences simultaneously. Hence, poor mental representations are constructed, which then lowers the long-term retention of information (Engle and Conway, 1998). Apart from this, if people have limited experience and prior knowledge, they may not be able to construct correct mental representations (Vosniadou and Brewer, 1992). Therefore, it is important to develop a method that can provide a simple and concise text structure for learners to understand narrative texts.

2.2 Lessons learned systems and narrative databases

With the development of information technology (IT), researchers have employed computational approaches to transfer lessons learned knowledge. NASA (2002) has adopted a lessons learned system to retain and disseminate valuable lessons regarding space development programs and projects. Information about a given lesson, such as an event that occurred, the lessons learned from dealing with the event and recommendations for future situations, is recorded. The lessons learned system and its content are organized by domain experts. The new lesson must be reviewed, approved and indexed by domain experts before being added to the system. The lessons learned system can send automatic notifications to users and support them in retrieving valuable experiential lessons through active searching.

Ferrada et al. (2016) highlighted that some of the main challenges faced by construction companies in transferring lessons learned knowledge are the absence of a systematic approach and a lack of organizational learning culture. It is also reported that current lessons learned systems adopt web-based platforms with searchable functions for users to retrieve valuable experiential lessons. However, current lessons learned systems are not widely accessed by users. Ferrada et al. (2016) proposed a mobile-based platform

that would incorporate information and communication technologies, cloud computing and knowledge management approaches to retain and disseminate valuable experiential lessons. The results indicated that the Internet infrastructure supporting the mobile access of the lessons learned system is not adequate in real situations. Apart from improving the system's functions and performance, it is also important to consider the human learning process so as to develop a learning culture within an organization.

Weber et al. (2001) stated that one of the reasons for the low utility rate of lessons learned systems is their limited functionality. Such systems only provide fundamental functions that assist users in searching for and retrieving valuable experiential lessons from the databases; they do not, however, facilitate users' learning and understanding of lessons learned knowledge. Most systems are domain-specific or organization-based standalone tools. Knowledge in different companies is stored in various databases with complex structures, which makes it difficult to share the valuable experiential lessons.

Apart from lessons learned systems, narrative databases can be used to capture and learn from narratives of past experiences (Snowden, 2002). Examples of good and bad practices, along with situations that resulted in success or failure, are reviewed, indexed and stored in narrative databases (Cheuk, 2007; Snowden, 2002). Narrative database can facilitate individuals to retrieve, reuse and analyze the knowledge of practitioners and pioneers. However, domain experts are required to spend a long time reviewing the narratives in order to complete the tagging and indexing processes. Moreover, narrative databases only provide fundamental search functions for users to retrieve narrative content; users need to assimilate the meanings of the narratives on their own (Snowden, 2002). Limited assistance or support is provided for users to understand and learn from the narratives, making it difficult for them to derive correct lessons learned knowledge. The shortcomings of narrative databases are similar to those of lessons learned systems.

The extant literature regarding lessons learned also highlights the need for domain experts to review, analyze and index the lessons learned documents or narratives. The process is time-consuming and labor-intensive. The lessons learned systems and narrative databases are established on different platforms with various interfaces and content structures. Users need to assimilate the meanings of the lessons learned documents or narratives on their own. As people have different learning capabilities, learners with insufficient prior knowledge often experience difficulties in grasping the right information from the narratives. Current lessons learned approaches have not yet investigated the human learning processes that support individuals in deriving correct lessons learned knowledge. Therefore, this paper attempts to introduce narrative

mapping and computational approaches such as natural language processing (NLP) and named entity recognition (NER) to help learners understand and incorporate correct lessons learned knowledge.

2.3 Narrative mapping and computational approaches

Narrative mapping has been proposed to address the needs of organizations in acquiring and representing lessons learned knowledge. Narrative mapping is designed to facilitate learners in understanding narrative content. Several characteristics of narrative maps work toward these purposes. First, unlike current computational approaches, which only concentrate on generating narratives with language understandable to humans, narrative maps also take into consideration the human learning process. The content of the narrative is normally based on real incidents, and the mapping identifies the narrative's characters, problems, events and actions. The process focuses on converting narratives into a simple and concise structure to help learners understand and construct mental representations of the narratives. The language of the narratives is based on the narrative sources and is understood by learners.

Researchers also indicate narrative mapping as an effective tool to aid readers in understanding narratives, especially the interrelationships among narrative elements (Derefinko et al., 2014; Beck and McKeown, 1981). The narrative map is also useful to improve human reading comprehension (Derefinko et al., 2014; Stringfield et al., 2011; Burke, 2004). Although narrative mapping can help users identify the characters, problems, events and actions in the narratives (Dimino et al., 1995), the traditional approach of narrative mapping is carried out by domain workers. Since different workers have different preferences and experiences, the quality of narrative mapping is hard to ensure.

In addition to a computational approach, a standardized framework to present narratives is needed to improve the situation. Cortazzi (2014) points out that there are different narrative models in the world. He indicates that Labov's model is the one that can systematically analyze internal narrative structure. Labov's model, advocated by Labov and Waletzky (1997), includes the components of abstract, orientation, complication, resolution, evaluation and coda. It has been used to analyze narratives in both written and oral forms (Özyıldırım, 2009). Narrative mapping with Labov's model can show a narrative in a simple and concise structure. Natural language processing (NLP) is one of the subareas of artificial intelligence (AI). It can help computers understand and respond to ambiguous natural human language (Negnevitsk, 2011). NLP's applications

include machine translation, speech recognition, information retrieval, information extraction and text summarization. Named entity recognition (NER) is defined as a task that detects proper nouns in atomic elements in documents and classifies them into predefined categories. It has been widely used in information extraction, response to questions and speech processing (Marrero et al., 2013). It aims at facilitating the extraction of deeper semantic or syntactic representation from a document (Béchet, 2011). This study attempts to investigate the use of NLP, NER and Labov's model in facilitating computational narrative mapping for lessons learned.

Existing NER approaches identify words in the documents based on predefined word lists. The NER processes only extract the words found on the predefined word lists, and the interrelationships between the extracted words are neglected. Narrative elements are different from named entities. Narrative elements and their interrelationships can help readers understand narratives. This study attempts to develop a computational approach that takes narrative or sentence structures into account to extract narrative elements and their interrelationships and conduct narrative mapping.

3. Methodology of computational narrative mapping for lessons learned

This section introduces the methodology of computational narrative mapping (CNM) for lessons learned. CNM is composed of three major components: narrative analysis, narrative element classification and narrative element organization. A narrative element classification algorithm (NECA) is proposed to investigate narrative elements in the form of concept 1–verb–concept 2 first. Then, named entity recognition (NER) is adopted to conduct narrative element classification and extraction. After analyzing narrative structures, keywords and rules are identified to conduct narrative element organization. The level of users' understanding of narratives is measured using a questionnaire and an experiment, both described in Section 4.

Fig. 1 shows the workflow of the CNM methodology. In the first step, narrative texts are preprocessed by a narrative analysis tool developed by Yeung et al. (2014). This tool divides a narrative text into sentences by a narrative segmentation method. It is constructed by detecting punctuation (such as full stops and question marks). A list of abbreviations (such as Mr., Dr., U.K., etc.) and pattern recognition rules to detect named entities (such as B. Obama, D. Trump, $0.99, 1997.7.1, etc.) are used to improve accuracy. The narrative segmentation method also classifies the sentences into three sections—beginning, middle and end—based on location (Yeung et al., 2014). The narrative analysis then reconstructs obscure and complex sentences into simple

sentences using a sentence restructuring method based on syntactic rules. By detecting punctuation and spaces, tokenization is carried out to divide a sentence into words (tokens). A part-of-speech (POS) tagger developed by Schmid (1994) is used to ascertain the POS of each word in each sentence. The resulting simple sentences contain a subject, a verb and an object. When the subject of a sentence is a pronoun, the method correlates the pronoun with a proper noun or noun phase.

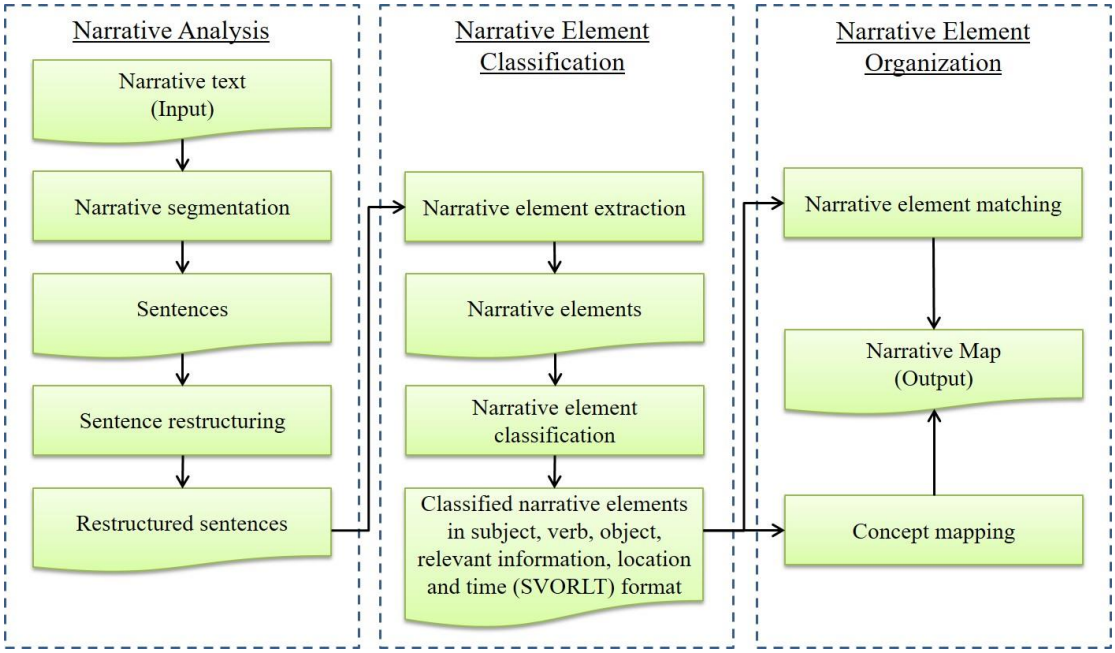


Fig. 1. The workflow of the computational narrative mapping (CNM) methodology for lessons learned

This study worked to develop the second and third steps of the CNM process. For the second step, a narrative element classification algorithm (NECA) is built, which is used to extract narrative elements from the restructured sentences. The extracted narrative elements are then classified into subject, verb, object, relevant information, location and time (SVORLT). In the third step, a narrative elements organization algorithm (NEOA) was designed and developed using heuristic rules based on Labov's model (Labov and Waletzky, 1997). NEOA is used to organize extracted narrative elements into a structured narrative representation. It also makes use of concept mapping to convert the essential parts of a narrative text into concept maps. The resulting narrative map is comprised of the narrative representation and the concept maps. The details of NECA and NEOA are described in Sections 3.1 and 3.2, respectively.

3.1 Narrative element classification

As mentioned above, the sentences restructured by the narrative analysis are divided into three sections based on their locations in the text, forming a beginning section, a middle section and an end section. In NECA, the sentences in the beginning section are arranged into a concept 1–verb–concept 2 pattern based on a concept mapping tool developed by Yeung et al. (2014). The concepts of the extracted sentences are then classified into six dimensions: subject, verb, object, relevant information, location and time (SVORLT). Name entity recognition (NER) and domain terminologies are used to facilitate the computational conversion to the SVORLT format. NER can classify atomic elements in text into predefined categories, such as the names of persons, locations and expressions of time. General architecture for text engineering (GATE), proposed by Cunningham et al. (2002), is one of the most commonly used NER toolkits (Al-Humaidi and Tan, 2010). The name entity word lists extracted from GATE are used to conduct name entity recognition.

Appendix A shows the names of word lists extracted from GATE. As different industries use unique terminologies, domain terminologies are needed to enhance the identification of narrative elements. A schematic diagram showing the construction process for domain terminologies is shown in Fig. 2. Experts first review domain literature to identify commonly used terminology. After summarization and analysis, the experts classify the terms into actors, things, locations and times.

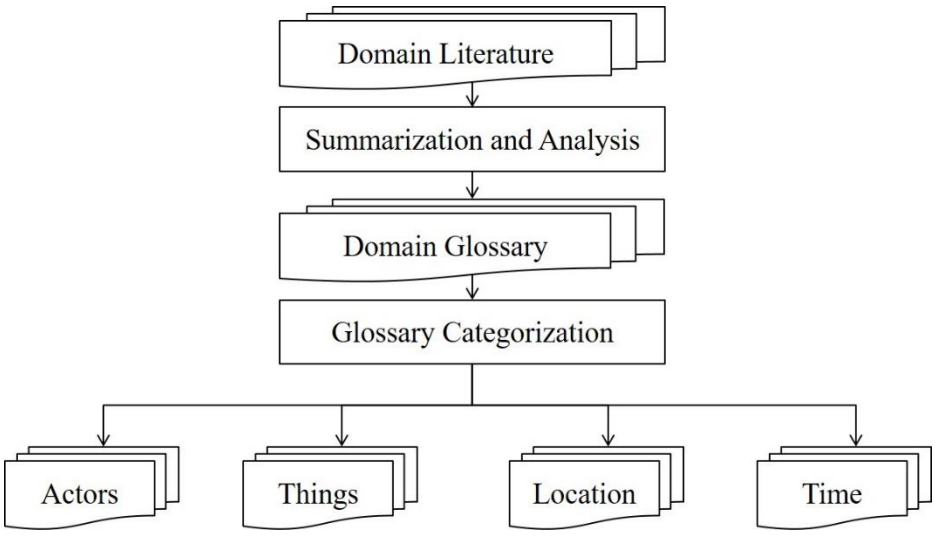


Fig. 2. A schematic diagram of the process of constructing domain terminologies

The narrative element classification algorithm (NECA) makes use of name entity word lists for persons, locations and times, and uses domain terminologies to classify narrative elements in order to convert them into the SVORLT format. The pseudo code

of the NECA is shown in Fig. 3. As each extracted narrative element is in the form of concept 1–verb–concept 2, the verb is selected and categorized into the verb dimension in the SVORLT format, and concept 1 is selected and classified into the subject dimension.

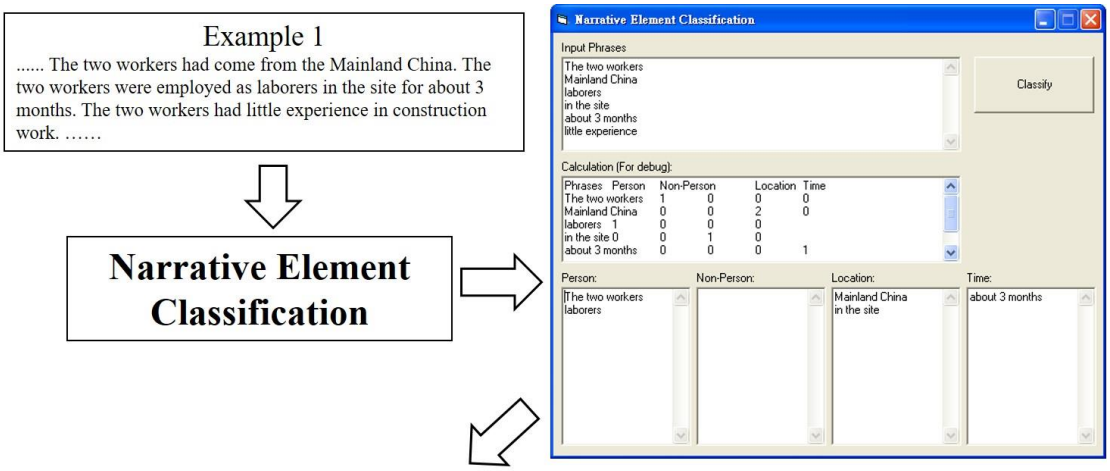
To further identify the personas and non-personas among the narrative elements, concept 1 is matched with the name entity word lists and glossary. If the text for concept 1 has a positive result in the name entity word lists—that is to say, if the person or text matches the terms in the glossary of actors—that text is classified as a persona in the subject dimension in the SVORLT format. If a text matches a term in the glossary of things, it is classified as a non-persona in the subject dimension in the SVORLT format. For concept 2, the object must be identified as a persona or non-persona, and location and time dimensions need to be identified in the SVORLT format. Each noun phrase in the text in concept 2 is selected. Each noun phrase is then matched with both the name entity word lists regarding persons, locations and time, and the defined glossary of actors, things, locations and time.

```
1.Select narrative element
2.Select verb in narrative element
3.  -Classify it as verb dimension
4.Select the text before verb (concept 1)
5.  -Classify it as subject dimension
6.  -Check it with name entity word lists  in the name of person & terms in glossary of actors
7.              -If it has a positive result
8.                              -Classify it as persona in subject dimension
9.              -Else check it with the terms in glossary of things
10.                             -If it has a positive result
11.                                             -Classify it as non-persona in subject dimension
12.                             -End
13.             -End
14.  Select the text after verb (concept 2)
15.  -Check it with name entity word lists in the name of location & terms in glossary of location
16.             -If it has a positive result
17.                             -Extract it & classify it as location dimension
18.              -End
19.   -Check it with name entity word lists in the name of time & terms in glossary of time
20.             -If it has a positive result
21.                             -Extract it & classify it as time dimension
22.              -End
23.   Select the remaining text after verb (concept 2)
24.   -Check it with name entity word lists in the name of persona & terms in glossary of actors
25.             -If it has a positive result
26.                             -Extract it & classify it as persona in object dimension
27.             Else check it with the terms in glossary of things
28.                             -If it has a positive result
29.                                             -Classify it as non-persona in object dimension
30.                             -End
31.              -End
32.Select the remaining text after verb (concept 2)
33. -Classify it as relevant information dimension
```

Fig. 3. Pseudo code of the narrative element classification algorithm

The algorithm then matches the noun phrases in concept 2 with the name entity word lists for locations and the terms found in the glossary of locations. If the noun phrases show a positive result, they will be extracted and classified into the location dimension in the SVORLT format. The noun phrases in concept 2 are then matched with the name entity word lists for expressions of time and the terms in the glossary of time-related words. If the noun phrases have a positive result, they will be extracted and classified as belonging to the time dimension in the SVORLT format. If the noun phrases have a positive result in the word lists for persons or the texts match terms in the glossary of actors, they are extracted and classified as personas in the object dimension in the SVORLT format. If the texts in concept 2 match the terms in the glossary of things, they are extracted and classified as non-personas in the object dimension in the SVORLT format. The remaining items of text in concept 2 are extracted and classified

in the relevant information dimension in the SVORLT format. An example is illustrated in Fig. 4.



Subject		Verb	Object		Relevant Information	Location	Time
Persona	Non-Persona		Persona	Non-Persona			
The two workers		had come from				Mainland China	
The two workers		were employed as	laborers			the site	about 3 months
The two workers		had			little experience in construction work.		

Fig. 4. Examples of narrative element classification

A narrative element classification system was built to conduct narrative element classification. The name entity word lists extracted from GATE and domain terminologies were extracted and entered into the narrative element classification system. In the example shown in Fig. 4, “The two main workers had come from the Mainland China” is the first sentence. The first sentence was divided into three parts by the MFACM method: concept 1, verb and concept 2. The algorithm identifies and extracts the verb part, “had come from.” The algorithm then selects concept 1—the word phrase “The two main workers”—and checks this text against the narrative element classification system. The word phrase “The two main workers” is concept 1. As it is a subject and is classified as a persona by the system, concept 1 is then recognized as a persona in the subject dimension in the SVORLT format. Concept 2 is “Mainland China,” and the system matches it to word lists of locations. It is recognized as the location dimension in the SVORLT format.

3.2 Narrative element organization

Narrative element organization based on Labov's model is conducted after narrative element classification. As mentioned by Labov and Waletzky (1997), the abstract is an optional element in narratives. In some cases, the abstract is absent from the narrative. If the abstract is present, a subtitle (such as "abstract," "summary," "recap," "outline," etc.) is used to indicate that it is a separate section. The separate section usually appears before the main text of the narrative. For orientation, the narrative's background information, such as personas, places and time, needs to be extracted. The background information can be found in the beginning section of the narrative. The complicating actions and resolution are events that can be extracted from the middle section. The evaluation, which indicates the reasons for telling the narrative, can be found in a middle or ending section. However, narratives do not always include evaluations. The coda contains the consequences of the narrative and can be found in the ending section. The narrative element organization algorithm (NEOA) is developed based on Labov's model to match the narrative elements and present them in a narrative map format.

The pseudo code of the NEOA is shown in Fig. 5. If it is present, the summary of the narrative texts is extracted by the algorithm and classified as the abstract. If the summary is absent, the title of the narrative texts is selected as the abstract. The narrative's orientation includes information about its personas, time and location. The extracted narrative elements, such as the persona in the subject and the time and location dimensions in the SVORLT format, are matched with the who, when and where dimensions in the narrative map, respectively. To facilitate computational narrative mapping, keywords and patterns are identified to extract information about the evaluation and resolution.

Table 1 shows the keywords and rules for narrative mapping. Keywords and rules are first extracted from the narrative sources and literature. The algorithm checks the sentences in the middle section. It identifies them as narrative evaluation if keywords that describe reasons are present (i.e., "because," "because of," "factor," etc.). The sentence describing the resolution is identified based on rules and keywords related to conduct and actions (such as "had to," "started to," "tried to," etc.). If a sentence in the middle section has any keywords describing actions, the algorithm identifies the text beginning with this sentence to the last sentence in the middle section as resolution. The remaining sentences in the middle section are extracted as complicating actions. If keywords describing conduct and actions are absent, the algorithm checks to see whether the sentences in the middle section begin with a person, such as a main persona, "worker," "workers," etc.

```
1.  //Abstract (optional)
2.  If summary of the narrative is present
3.          -Select it & match it to abstract in narrative map
4.  Else
5.          -Select the title of the narrative & match it to abstract in narrative map
6.  End
7.  //Orientation including persona, time and place
8.  If persona in subject dimension is present
9.          -Select it & match it to who in narrative map
10. End
11. If time dimension is present
12.         -Select it & match it to when in narrative map
13. End
14. If location dimension is present
15.         -Select it & match it to where in narrative map
16. End
17. //Evaluation (optional)
18. Select sentences in middle section
19. If the sentence has key phrases regarding reasons
20.         -Select it & match it to evaluation in narrative map
21. End
22. //Resolution
23. Select sentences in middle section
24. Check from the last sentence in the middle section
25. If the sentence has key phrases regarding actions
26.         -Select from the identified sentence to the end in the middle section
27.         -Extract them & match them to resolution in narrative map
28. Else
29.         -Identify the last sentence with pattern regarding actions in the middle section
30.         -Select the identified sentence to the end in the middle section
31.         -Extract them & match them to resolution in narrative map
32. End
33. //Complication
34. Match the remaining sentences in the middle section to complication in narrative map
35. //Coda
36. Select the sentences in end section & match them to coda in narrative map
37. //Description of orientation
38. Match the graph with concepts and linkages to description of orientation in narrative map
```

Fig. 5. Pseudo code of narrative element organization algorithm

The algorithm performs this check beginning with the last sentence in the middle section. If the sentence beginning with a person is found, the algorithm further checks if any successive sentences begin with a person. If no successive sentences begin with a person, the sentences starting from the identified sentence to the end of the middle section are extracted as resolution, and the remaining sentences in the middle section are extracted as complicating actions. If there is a successive sentence that begins with a person, this successive sentence is selected and further checked by the algorithm.

Table 1. Keywords and rules for narrative mapping

Narrative Mapping	Keywords	Rules

Abstract (Summary, optional)	Nil	Extract abstract if it is present or extract title of the narrative texts if abstract is absent.
Orientation (Person, location and time)	Nil	Extract narrative elements, such as persona in subject, time and location dimension in SVORLT format and match them with who, when and where in orientation.
Complicating Action (What happened)	Nil	Extract sentences in the middle section after extracting resolution.
Resolution (Actions have been taken)	Keywords regarding conduct and action, such as had to, started to, tried to, etc.	Extract successive sentences beginning with person, such as main persona, worker, workers, etc., from the end of the middle section if keywords regarding conduct and actions are absent.
Evaluation (Reason to tell the narrative, optional)	Keywords regarding reasons, such as because, because of, reason, factor, etc.	Nil
Coda (Consequence)	Nil	Extract the sentences in the end section as coda.

If the identified keywords and rules are absent, domain workers will be asked to further review the sentences. New keywords or rules are stored for future use after approval. After the evaluation and resolution are identified, the remaining sentences in the middle section are selected as complicating actions. The sentences in the end section are chosen as coda. Finally, the algorithm matches the graph with concepts and linkages generated from the information in the narrative's beginning section to the detailed orientation in a narrative map. An example of a narrative map (a narrative mapping output) is shown in Fig. 6. This map uses Labov's model to indicate a narrative's abstract, orientation, complicating actions, resolution, evaluation and coda. Graphs with concepts and linkages between narrative elements are also shown in a narrative map to help readers better understand the narrative.

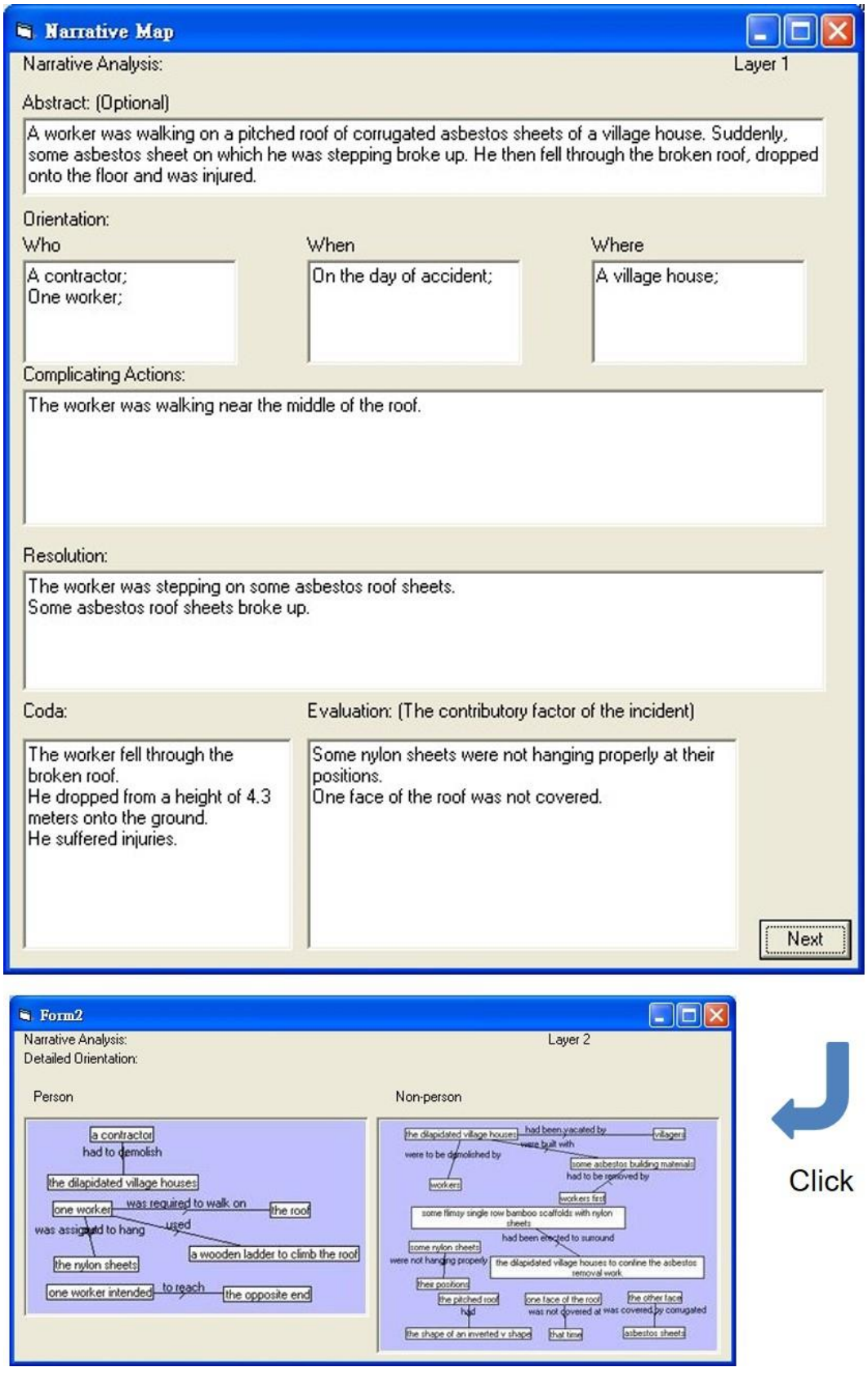


Fig. 6. An example of a narrative mapping output

4. Evaluation methods

To evaluate the performance of the CNM approach, both case-based and experiment-based evaluations were conducted. The case-based evaluation aimed to measure user satisfaction with the CNM approach in the construction industry. The experiment-based evaluation attempted to measure the recall and precision of the CNM approach when extracting narrative elements using real-life narratives from a reminiscence study. The CNM approach was compared with the human gold standard and the GATE approach. The details of the case-based and experiment-based evaluations are described in Section 4.1 and Section 4.2, respectively.

4.1 Case-based evaluation

This section explains how to conduct a case study to measure user satisfaction with the CNM approach in a real situation. The CNM approach has been implemented on a trial basis in the construction industry. The construction industry is known as one of the most high-risk industries in the world due to its high rate of fatalities and accidents (Al-Humaidi and Tan, 2010). The situation in Hong Kong is particularly acute. The construction industry recorded the highest number of accidents and fatalities out of Hong Kong's sectors (Labor Department, 2016). Several factors contribute to this phenomenon, the main one being that safety records and documents in the construction industry are improperly organized and regularly lost. The construction sector's track record in this regard is much worse compared with other sectors in Hong Kong. This results in untraceable working practices and conditions at construction sites, complicating the acquisition of lessons learned knowledge. Construction workers in Hong Kong, especially those working on the frontlines, are often illiterate or less educated people. It is difficult for them to understand the importance of safety issues and leverage the tools to ensure workers' health and safety. In addition, the turnover rate of construction workers in Hong Kong is high, further complicating the build-up of lessons learned knowledge (Choi et al., 2012).

Due to the increasing demand for construction manpower, good remuneration packages and promotion prospects, many graduates in tertiary education go on to develop careers in the construction industry (Taylor, 2015). New hires who are unfamiliar with the working environment of the construction site are at a high risk of injury. Therefore, it is important to motivate and educate construction workers, some of them may be illiterate in many parts of the world, to follow safety guidelines.

Other than the traditional trial-and-error approach, acquiring lessons learned from narratives about previous incidents helps humans to learn from past experiences in a safe environment. Moreover, it has been proven that a narrative map is a useful tool to teach laymen to understand narratives (Burke, 2004). For these reasons, the construction industry was chosen as a reference site in this study. Raw data from the industry were collected in the form of narratives about incidents in which workers fell from heights. The raw data were then processed by CNM to produce narrative maps.

In this study, a narrative presentation questionnaire was designed and used to measure user satisfaction with the content and presentation of the generated narrative maps. This narrative presentation questionnaire (evaluation A) was modified from Shi (2012). Evaluation A contained three different formats: a traditional paragraph-based format, a format using concept maps and a format using the narrative maps under evaluation in this study. The traditional paragraph-based format displayed narratives presented in paragraphs. The format using concept maps presented narratives in the form of concepts with linkages. The narrative map depicted narratives using Labov's model and indicated the relationships between concepts. All formats in evaluation A were constructed based on real narratives from the construction industry. Appendix B shows the narrative presentation evaluation questionnaire. Figs. a, b and c–e in Appendix B show the three different formats, respectively.

The questions in evaluation A and their short forms are shown in Table 2. Participants were asked to answer Q1 to Q6 in response to each format and to answer Q7 for all three formats. The questionnaire adopted the five-point Likert scale (5 = very easy/strongly agree; 4 = easy/agree; 3 = neutral; 2 = difficult/disagree; 1 = very difficult/strongly disagree) for Q1 to Q6. For Q7, participants were required to select one scenario among three.

Q1 and Q2 were used to investigate how the presentation layout assisted the participants in reading and understanding the narratives. Q3 and Q4 were related to information extraction and association, while Q5 and Q6 were about learning from the texts, as shown in the presentation layouts. The text-based options were converted to numerical scores in order to support quantitative analysis. This five-point scale ranged from 2 (very easy) to -2 (very difficult) for questions assessing difficulty and from 2 (strongly agree) to -2 (strongly disagree) for questions gauging level of agreement A higher score indicates that the corresponding option has greater positive strength.

Table 2. Questions for narrative presentation evaluation

	Questions for Narrative Presentation Evaluation	Short Forms of the Questions
Q1	With the texts provided to you, do you think that they are easy to read or understand?	Easy to read/understand
Q2	To what extent do you agree that this way of presentation enables you to understand the texts based on people, locations, time or other concepts?	Understand people, locations, time/other concepts
Q3	To what extent do you agree that this way of presentation enables you to extract relevant information from the texts?	Extract relevant information
Q4	To what extent do you agree that this way of presentation enables you to extract relevant information from your memory?	Extract relevant information
Q5	To what extent do you agree that this way of presentation enables you to learn the important issues from the texts?	Learn the important issues
Q6	To what extent do you agree that this way of presentation enables you to remember the important issues from the texts?	Remember the important issues
Q7	Which presentation way will help you most understand the narratives and learn the correct lessons?	Understand narratives and learn the correct lessons

4.2 Experiment-based evaluation

This section describes the experiment that was designed and conducted to test the narrative element classification capability of CNM and an existing tool named general architecture for text engineering (GATE) (Cunningham et al., 2002). GATE is a mature graphical development tool for conducting natural language processing tasks such as information extraction. It first uses a tokenizer to split text into simple tokens such as words, numbers and punctuation. Then it uses sentence splitter to divide the text into sentence. A part-of-speech (POS) tagger is used to tag each token with its correct POS. After that, a gazetteer is used to identify the special terms in the domain to facilitate the information extraction process.

In order to conduct the experiment-based evaluation, experts were invited to construct the human gold standard of information regarding peoples' names, locations and expressions of time. The experts were required to review documents and divide relevant information into categories, including peoples' names, locations and expressions of time. The human gold standard constructed by the experts was then used as the model answer for comparing the results of GATE and CNM.

GATE was selected as the baseline tool due to its structured user interface. CNM's

performance in narrative element classification was compared with the baseline algorithm in GATE, which can identify information regarding people's names, locations and expressions of time. In CNM, the extracted narrative elements were entered into the narrative element classification module and classified into person, location and time categories. Fig. 7 shows the experimental flow of the narrative element classification evaluation. The evaluation of the narrative classification (evaluation B) was designed to compare the performance of CNM and GATE regarding their accuracy in classifying narrative elements.

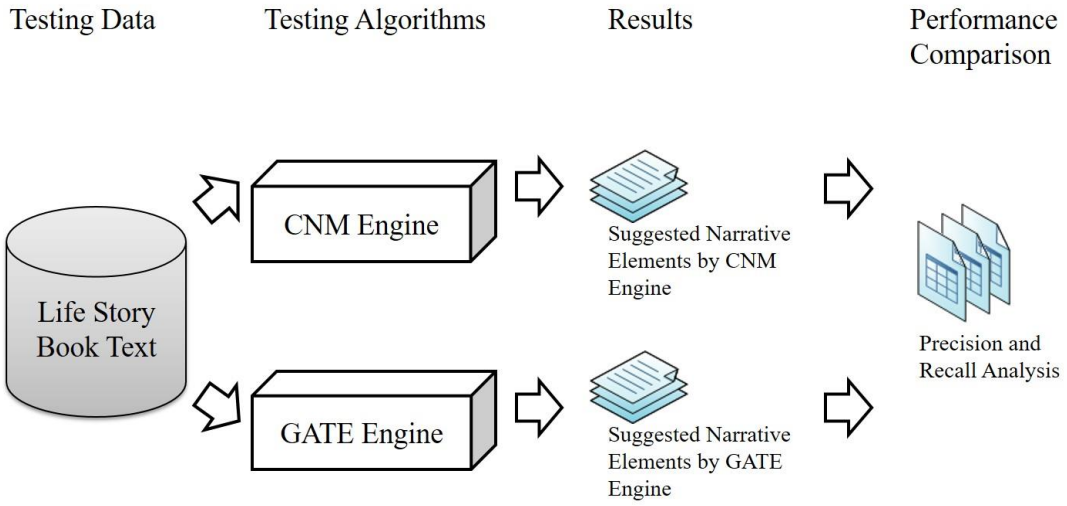


Fig. 7. Experimental flow for narrative element classification evaluation

Precision, recall and the f-measure of the number of narrative elements were measured. Equation (1), Equation (2) and Equation (3) were used to calculate precision, recall and the f-measure, respectively. Precision refers to the ratio of retrieved items which are true positive to the retrieved items, while the recall is the ratio of retrieved items which are true positive to all relevant items. The f-measure acts as a harmonic mean of precision and recall. In this study, the f-measure was calculated by Equation (3), and precision and recall were equally weighted. Personal life story book texts collected by Shi (2012) were used as textual data. The texts which recorded a person's important life experience was used for providing reminiscence support. One of the reasons for this is that the content of these narratives described relatable human lives, and they were thus simple and easy to understand. The narrative texts also contained rich information regarding personal names, locations and time, which was useful for evaluation B.

$$Precision = \frac{|\{\text{relevant narrative elements}\} \cap \{\text{retrieved narrative elements}\}|}{|\{\text{retrieved narrative elements}\}|}$$

(1)

$$Recall = \frac{|\{\text{relevant narrative elements}\} \cap \{\text{retrieved narrative elements}\}|}{|\{\text{all relevant narrative elements}\}|}$$

(2)

$$F = 2 \cdot \frac{(\text{Precision} \cdot \text{Recall})}{\text{Precision} + \text{Recall}}$$

(3)

5. Results and discussion

This section discusses the results of the evaluations of the CMN methodology. The case-based evaluation (evaluation A) and experiment-based evaluation (evaluation B) are presented in Sections 5.1 and 5.2, respectively.

5.1 *Case-based evaluation results*

The evaluation of narrative presentation (evaluation A) measured user satisfaction with the presentation layouts generated by the traditional paragraph-based and concept mapping approaches, as well as by CNM. In evaluation A, 30 participants were invited to evaluate the three narrative presentation layouts with apurposely designed questionnaire (see Appendix B). The questionnaire included three scenarios. Scenario A was a narrative presented in a traditional paragraph-based format. Scenario B was the concept map generated from the narrative mentioned in Scenario A, while Scenario C showed the narrative map constructed by CNM, based on the same narrative.

The profiles of these 30 participants in this evaluation A are shown in Table 3. Of these 30 participants, the ratio between males and females was 1:1. Respondents were mainly between 20 and 24 years of age, and most were enrolled in a degree program in Hong Kong. The remaining participants were degree holders or were enrolled in a master's program in Hong Kong or Europe. In terms of the participants' level of English, 20% (primarily from Europe) said they were at an advanced level, 20% said they were at an elementary level and 60% said they were at an intermediate level. However, the medium of instruction in universities in Hong Kong is English, and as the respondents were currently students of tertiary education in Hong Kong, their level of English was adequate for this evaluation. Most had less than one year of work experience, and only a few had more than one year. Lastly, about 27% had prior knowledge of the

construction industry, while the remaining 73% did not.

Table 3. Profiles of participants in evaluation A (regarding narrative presentation)

	Category (Percentage)	
Gender	Male (50%)	Female (50%)
Age group	20-24 (63.33%)	25-29 (33.33%)
	30-34 (3.33%)	
Home country	Hong Kong (70%)	China (23.33%)
	Other (6.67%)	
Education	Degree holder / currently in a degree program (66.67%)	Master degree holder / currently in a master's degree program (23.33%)
	Doctorate degree holder / currently in a doctoral degree program (10%)	
English level	Elementary (13.33%)	Intermediate (70%)
	Advanced (16.67%)	
Working experience	Less than one year (56.67%)	One to three year(s) (26.67%)
	More than three years (16.66%)	
Prior knowledge of safety in construction industry	Yes (26.67%)	No (73.33%)

The results of evaluation A are shown in Fig. 8. The percentages in the table represent the proportion that was selected among the relevant options. A higher percentage means that the option was selected by more participants. To facilitate data analysis, these percentage-based results were then converted to relevant average scores, which are shown in Fig. 9. The average scores indicate that the respondents found that the narrative map layout made narrative texts easier to read and understand than the traditional paragraph-based and concept map layouts.

The concept map and narrative map layouts also enabled users to understand the text based on people, locations, time or other concepts. The average scores of the narrative map approach are much higher than those for the concept map approach for Q1 and Q2 (see Fig. 9). Q3 and Q4 were intended to elicit information about how the presentation layouts support the information extraction and association processes. Generally, similar responses were obtained in Q3 and Q4 from the participants. The respondents agreed that both the concept map and narrative map layouts helped them to extract relevant information from the texts and from their memories. The narrative map approach obtained the highest scores out of the three approaches.

As indicated in Fig. 8c, over 55% of the respondents felt that the paragraph-based approach could not help them extract relevant information from the texts. On the other hand, 50% of the respondents agreed that the narrative map approach helped them extract relevant information from the texts (see Fig. 8c) and from their memory (see Fig. 8d). In terms of learning, the respondents gave more negative feedback about the traditional paragraph-based approach than for the other two approaches (see Fig. 8e and 8f). This indicates that the respondents generally did not agree that the traditional paragraph-based approach can help them to learn or remember the important issues from the texts. The respondents were in favor of the narrative map approach. They agreed that the narrative map approach performed best among the three approaches in facilitating learning and strengthening memory regarding important issues from the narrative texts. For Q7, respondents were invited to select the presentation layout that most helped them understand the narratives and learn the correct lesson. Over 90% of the respondents chose the narrative map approach (see Fig. 8g).

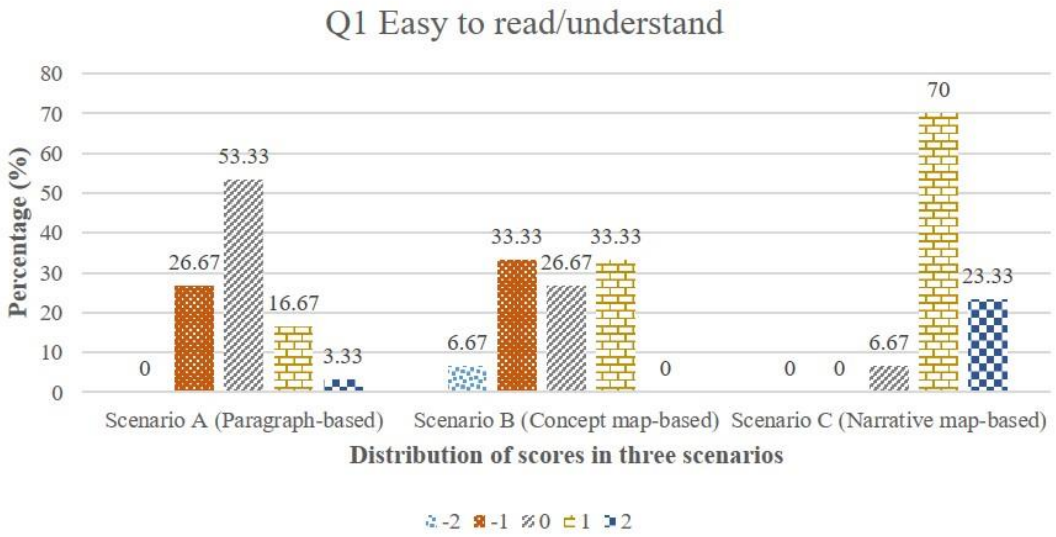


Fig. 8a. Distribution of scores for Question 1 in the narrative presentation evaluation

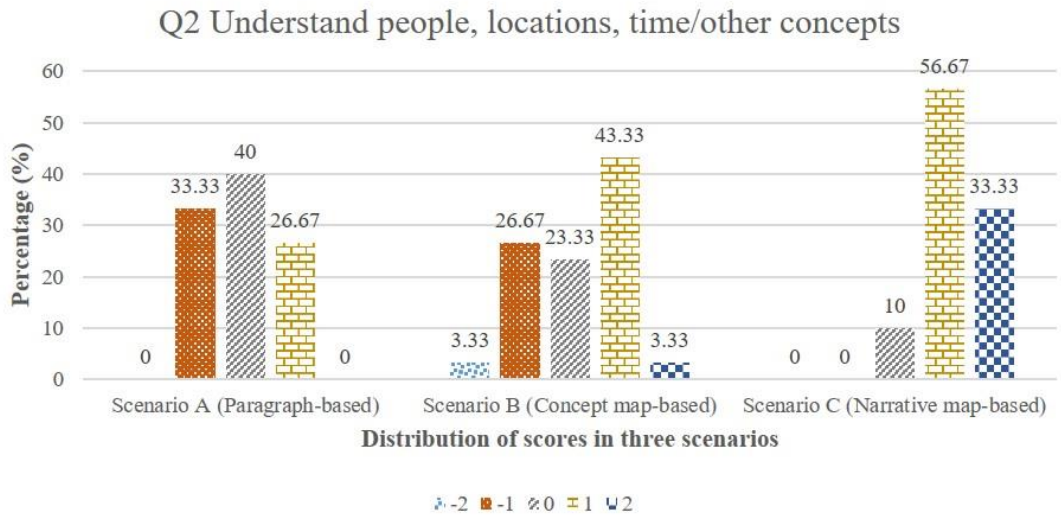


Fig. 8b. Distribution of scores for Question 2 in the narrative presentation evaluation

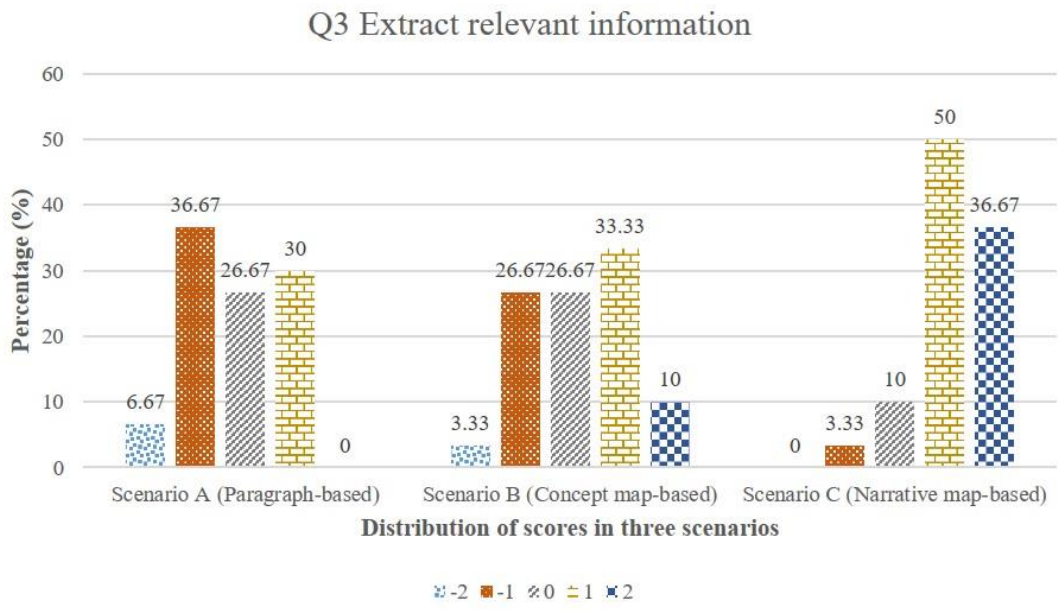


Fig. 8c. Distribution of scores for Question 3 in the narrative presentation evaluation

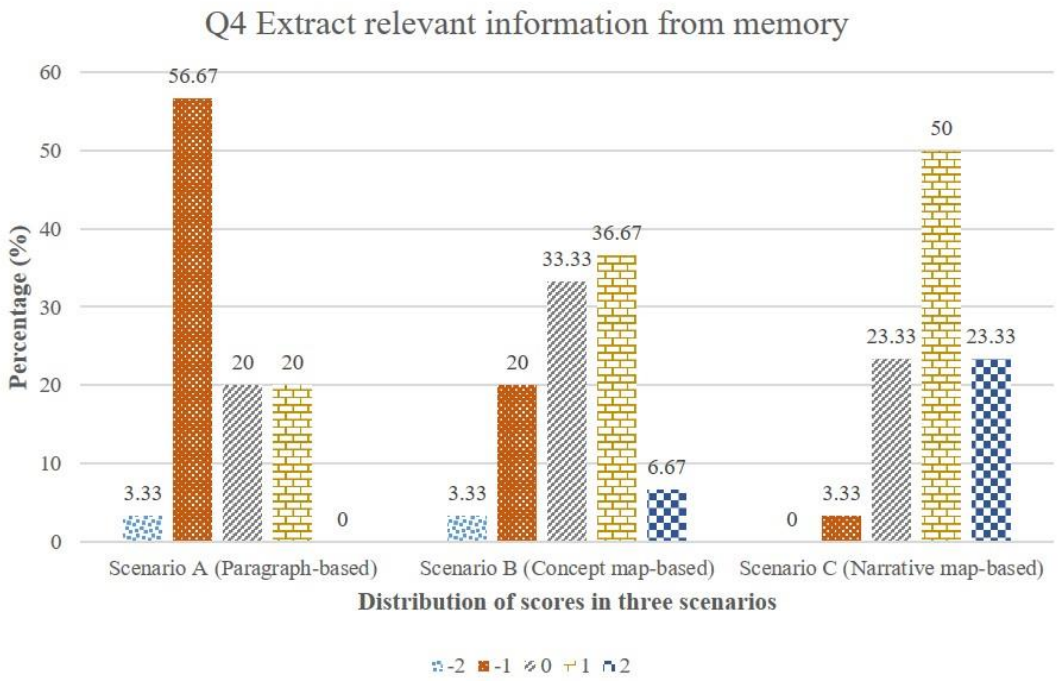


Fig. 8d. Distribution of scores for Question 4 in the narrative presentation evaluation

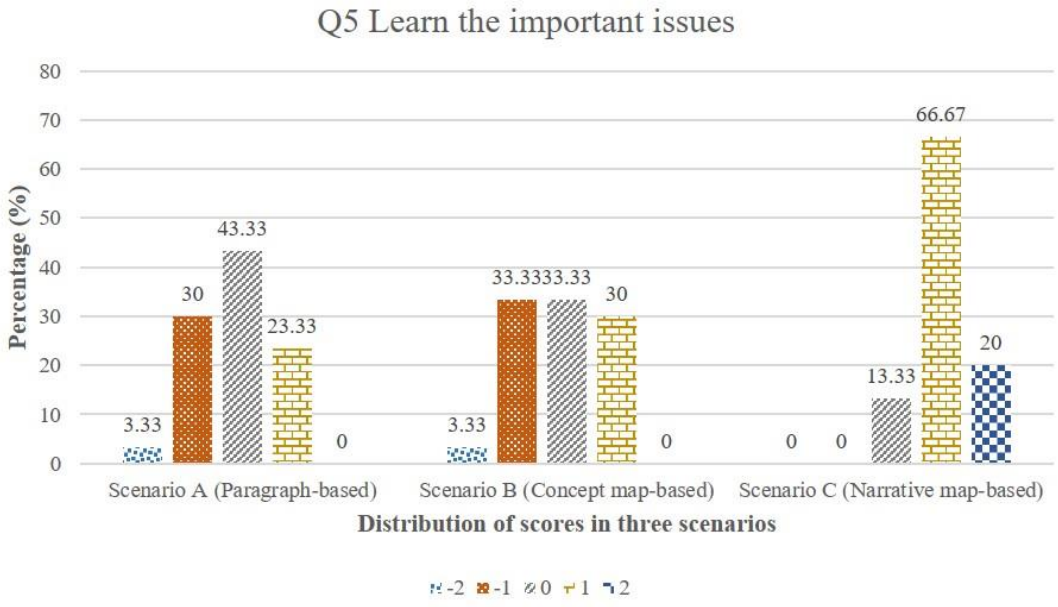


Fig. 8e. Distribution of scores for Question 5 in the narrative presentation evaluation

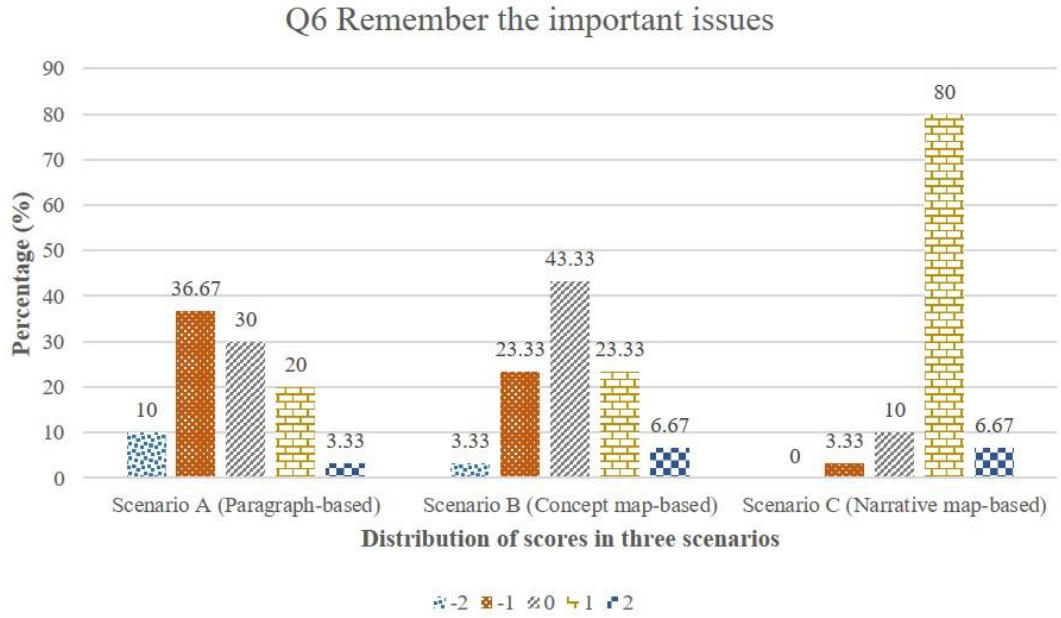


Fig. 8f. Distribution of scores for Question 6 in the narrative presentation evaluation

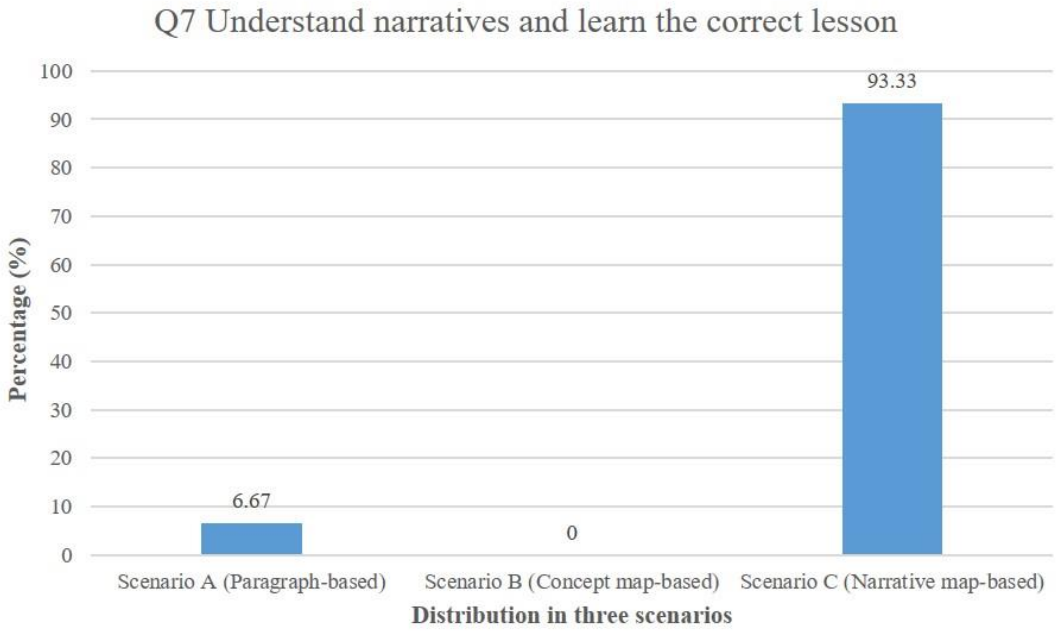


Fig. 8g. Distribution of scores for Question 7 in the narrative presentation evaluation

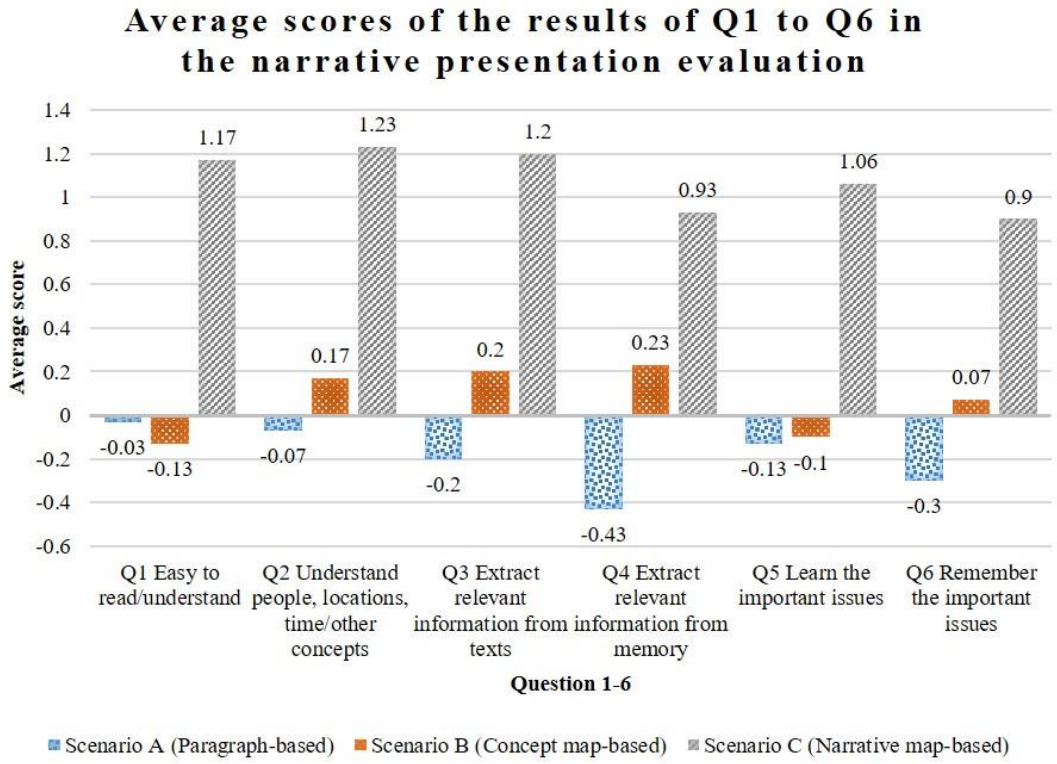


Fig. 9. Average scores for Questions 1 to 6 in the narrative presentation evaluation

5.2 *Experiment-based evaluation results*

For the evaluation of the narrative classification (evaluation B), narrative elements were extracted from 47 narratives in a personal life story book. Among the collected narratives, it was found that 58 sentences were not related to personal life stories. Hence, 109 sentences relating to personal life stories were used to form the main texts of the evaluation data. The results of evaluation B are shown in Table 4, Fig. 10 and Fig. 11. The results (see Table 4) show that CNM performed better than the baseline GATE algorithm. CNM was found to maintain a higher precision rate and a higher recall rate than the baseline algorithm.

Table 4. Evaluation results of the proposed method in narrative element classification

Average Accuracy	Baseline GATE Method	CNM
Average precision (personal life story book texts)	55.8%	75.7%
Average recall (personal life story book texts)	48.3%	75.4%
Average f-measure (personal life story book texts)	49.5%	74.9%

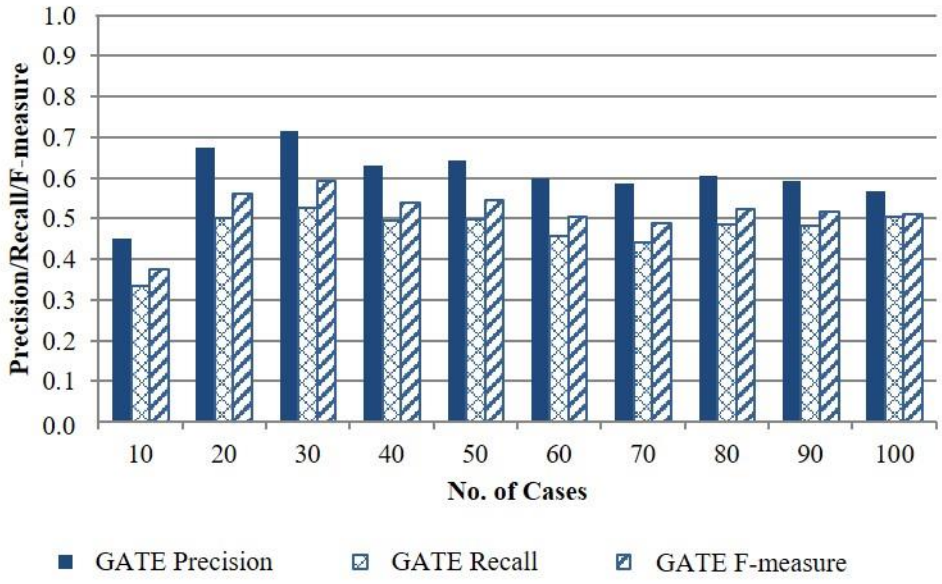


Fig. 10. Evaluation results of GATE in narrative element classification

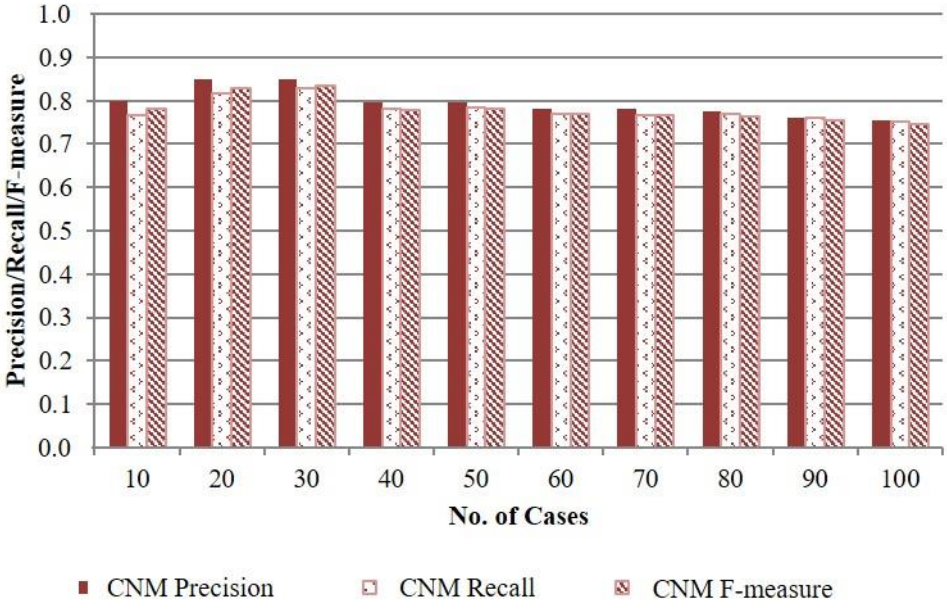


Fig. 11. Evaluation results of CNM in narrative element classification

6. Conclusion

This paper introduces the concept of computational narrative mapping (CNM) and its effectiveness in the real world. The novelty of this paper lies in the systematic mapping method it proposes to construct narrative maps for acquiring and representing lessons learned knowledge. The traditional manual narrative mapping approach is inconsistent,

time-consuming, labor-intensive, and knowledge-intensive. A computational method to automatically conduct narrative mapping and generate narrative maps is developed and evaluated.

The key contributions of this research work include:

- A novel method of narrative mapping, which employs narrative maps to represent lessons learned knowledge in order to help learners better understand narratives of past experiences.
- An advanced computational narrative mapping (CNM) method developed to automate the proposed narrative mapping and thereby facilitate the narrative map construction process.
- Two novel algorithms developed to automatically convert narrative texts into narrative maps. The CNM system incorporates the technologies of natural language processing (NLP) and name entity recognition (NER) to automatically conduct narrative elements classification and narrative mapping.
- A narrative map constructed based on Labov's model. This narrative mapping output, which presents a narrative using a simple and concise structure, can help represent lessons learned knowledge.
- A prototype of a CNM system was constructed and trial implemented in the construction industry. A questionnaire was designed to evaluate how users understand narratives and gain the correct lessons learned from the output of CNM.
- A case-based evaluation was conducted to measure user satisfaction with the content and presentation of the generated narrative maps, and an experiment-based evaluation was conducted to compare the capability of CNM with an existing tool. For the case-based evaluation, the performance of CNM was evaluated by comparing its output with narrative texts presented in the forms of the traditional paragraph and the concept map. Over 90% of the respondents agreed that the narrative map approach helped them better understand the narratives and learn the correct lesson. For the experiment-based evaluation, CNM was found to maintain a higher precision rate and a higher recall rate as compared to the baseline algorithm.

CNM can analyze text-based narratives and producing new narrative presentation layouts for narrative retention and lessons learned. This study focused on investigating text-based narratives in a high-risk industry. It was shown that the proposed CNM can facilitate knowledge retention and lessons learned within an organization.

Further work is required to advance three important aspects. First, the CNM method currently relies on using expert rules to conduct narrative mapping. Further studies can adopt machine learning to enhance the current approach, using this study's dataset as a training set. Second, the current version of CNM has been trial implemented in the construction industry to help learners derive correct lessons learned from narratives. In the future, CNM can be extended as an evaluation tool for teachers or trainers to evaluate students' understanding of narratives. Once students have prepared their narrative maps on their own after reading the narratives, teachers and trainers can promptly provide the narrative map produced by CNM as a standard answer for explanation or to measure students' understanding of the narratives. Third, information overload is an increasingly serious problem. CNM can be applied to analyze or summarize narrative-based news or articles. The results from various sources of information can be compared and summarized to extract key information for learning or decision-making.

Acknowledgements

This work was supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. PolyU 514509). The authors would also like to express their sincere thanks to the Research Committee of the Hong Kong Polytechnic University for the financial support of the project through a Ph.D studentship (Ref. no. RPKX). Many thanks are also due to the Construction Industry Council (CIC) of Hong Kong for its technical support.

Appendix A. Name entity word lists extracted from GATE

Name entity word list		
ANNIE Gazetteer		
Person	Location	Time
person_ambig.lst	airports.lst	date_key.lst
person_ending.lst	city.lst	date_unit.lst
person_female.lst	city_cap.lst	day.lst
person_female_cap.lst	country.lst	day_cap.lst
person_full.lst	country_abbrev.lst	festival.lst
person_male.lst	country_cap.lst	hour.lst
person_male_cap.lst	loc_generalkey.lst	months.lst
person_relig.lst	loc_key.lst	ordinal.lst
person_sci.lst	loc_prekey.lst	time.lst
surname_prefix.lst	loc_prekey_lower.lst	time_arpm.lst
	loc_relig.lst	time_modifier.lst
	mountain.lst	time_unit.lst
	person_ending.lst	time.lst
	province.lst	timezone.lst
	racecourse.lst	year.lst
	region.lst	
	region_cap.lst	
	region_uk .lst	
	Water.lst	

Appendix B. Narrative presentation evaluation questionnaire

QUESTIONNAIRE

Narrative Presentation Evaluation

The aim of the questionnaire is to gather information for the purpose of continuous improvement of the designed computational narrative analysis system. It is composed of two parts which are personal information and narrative presentation evaluation. It would be appreciated if you could spend some time to complete this questionnaire. All information provided is confidential and strictly for the above purpose.

Part I - Personal Information

Please insert "√" in the box or fill in the following information.

1. What is your gender?	Male ☐	Female ☐
2. How old are you?	20-24 ☐	25-29 ☐
	30-34 ☐	35-39 ☐
	40-44 ☐	45-49 ☐
	50-54 ☐	55-59 ☐
	Other ☐	
	Please specific: _____	
3. Where do you come from?	Hong Kong ☐	China ☐
	Other ☐	
	Please specific: _____	
4. What is your educational level?	Certificate ☐	Diploma ☐
	Higher Diploma ☐	Bachelor ☐
	Master ☐	Doctor ☐
	Other ☐	
	Please specific: _____	
5. What is your level of English?	Elemental ☐	Middle ☐
	Advanced ☐	
6. How much full time working experience do you have?	Year(s) : _____	
	Month(s) : _____ (0-11 months)	
7. Do you have any prior knowledge about construction industry?	Yes ☐	No ☐

Part II – Narrative Presentation Evaluation

Individuals always gain knowledge or experience through reading narratives from their predecessors. However, due to the variation of human capability, different persons may have different understandings or interpretations after reading the same texts. It may cause them to make the wrong interpretations or learn incorrect lessons. To address these problems, a computational narrative analysis system is designed to analyze the narratives and facilitate individuals to understand and learn the narratives' content.

The objective of this evaluation is to measure user satisfaction of narrative presentation styles generated by the system. The scenario applied in this experiment contains three types of presentation: (i) narrative in paragraph-based, (ii) narrative in concept map, and (iii) narrative in narrative map. For this experiment, please read the scenario description carefully, and then answer the relevant questions (please note the experiment takes around 15 minutes).

Experiment 1 - Scenario 1-A

Figure A shows the narrative in traditional paragraph-based presentation. Please read the texts in Figure A carefully and answer questions Q1-A1 to Q1-A6.

A contractor had to demolish some dilapidated village houses which had been vacated by villagers. Some of these houses were built with asbestos building materials and these materials had to be removed first before the houses were to be demolished. Prior to the day of the accident, some flimsy single row bamboo scaffolds with nylon sheets had been erected to surround the houses in order to confine the asbestos removal work.

On the day of the accident, it was discovered that some nylon sheets were not hanging properly at their positions. One worker was assigned to hang the sheets back to their designated positions. The pitched roof had the shape of an inverted V. One face of the roof was not covered while the other face was covered by corrugated asbestos sheets. He used a wooden ladder to climb up the roof. In order to reach the opposite end and put the nylon sheets back to their designated positions at that end, he was required to walk on the roof. When he was walking near the middle of the roof, some asbestos roof sheets on which he was stepping on broke up. He fell through the broken roof, dropped from a height of 4.3 meters onto the ground and suffered injuries.

Figure A: Scenario 1-A – Narrative in traditional paragraph-based presentation

Q1-A1 With the texts provided to you, do you think that it is easy to read or understand? (Please choose one of the following.)

☐ Very easy ☐ Easy ☐ Neutral ☐ Difficult ☐ Very difficult

Q1-A2 To what extent do you agree that this way of presentation enables you to understand the texts based on people, locations, time or other concepts? (Please choose one of the following.)

☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree

Q1-A3 To what extent do you agree that this way of presentation enables you to extract relevant information from the texts? (Please choose one of the following.)

☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree

Q1-A4 To what extent do you agree that this way of presentation enables you to extract relevant information from your memory? (Please choose one of the following.)

☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree

Q1-A5 To what extent do you agree that this way of presentation enables you to learn the important issues from the texts? (Please choose one of the following.)

☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree

Q1-A6 To what extent do you agree that this way of presentation enables you to remember the important issues from the texts? (Please choose one of the following)

☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree

Experiment 1 - Scenario 1-B

Figure B shows the concept map developed based on the narrative texts in Scenario 1-A. Please read the texts in Figure B carefully and answer questions Q1-B1 to Q1-B6.

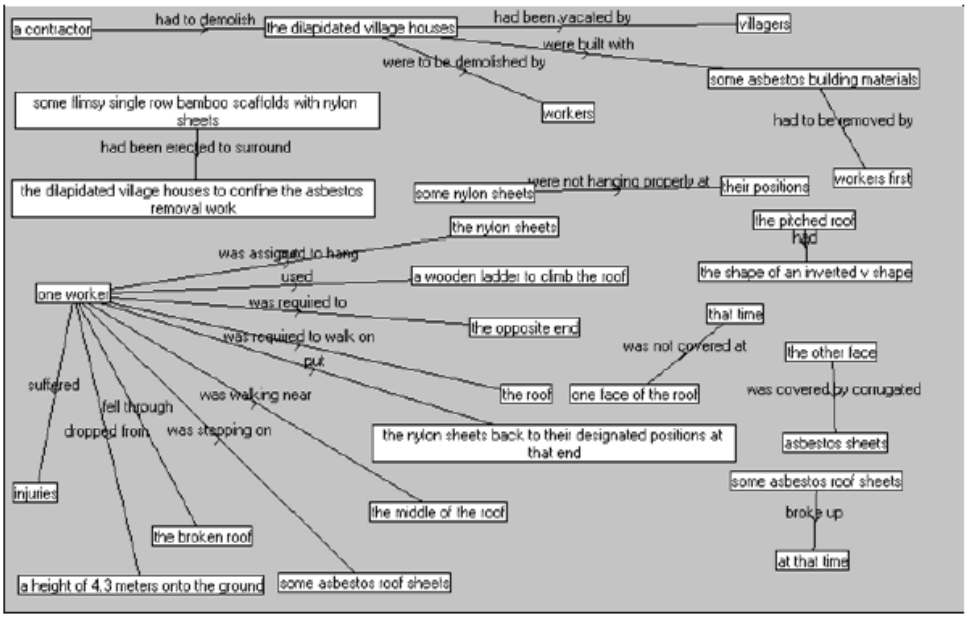


Figure B: Scenario 1-B – Narrative in concept map presentation

Q1-B1 With the texts provided to you, do you think that it is easy to read or understand? (Please choose one of the following.) ☐ Very easy ☐ Easy ☐ Neutral ☐ Difficult ☐ Very difficult
Q1-B2 To what extent do you agree that this way of presentation enables you to understand the texts based on people, locations, time or other concepts? (Please choose one of the following.) ☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree
Q1-B3 To what extent do you agree that this way of presentation enables you to extract relevant information from the texts? (Please choose one of the following.) ☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree
Q1-B4 To what extent do you agree that this way of presentation enables you to extract relevant information from your memory? (Please choose one of the following.) ☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree
Q1-B5 To what extent do you agree that this way of presentation enables you to learn the important issues from the texts? (Please choose one of the following.) ☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree
Q1-B6 To what extent do you agree that this way of presentation enables you to remember the important issues from the texts? (Please choose one of the following.) ☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree

Experiment 1 - Scenario 1-C

Figure C shows the narrative map developed based on the narrative texts in Scenario 1-A. The narrative map form includes layer 1 and layer 2. Layer 1 as shown in Figure C shows the general information about the narrative including abstract (summary of the incident), orientation (information regarding characters, time and location), complication action (the events that trigger the incident), resolution (characters' action), coda (consequence of the incident) and evaluation (the meaning of the incident). Layer 2 of the narrative map form is shown after clicking the "Next" button in layer 1. Figures D and E show the detailed information about the characters and objects in layer 2 respectively. Please read the texts in Figures C, D and E carefully and answer questions Q1-C1 to Q1-C6.

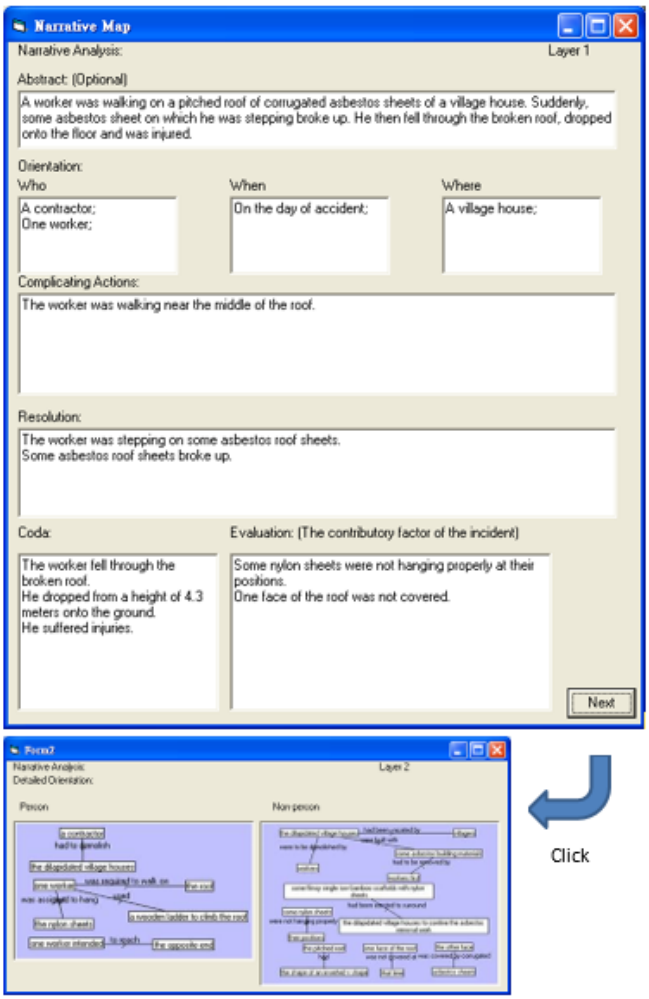


Figure C: Scenario 1-C – Narrative in narrative map presentation

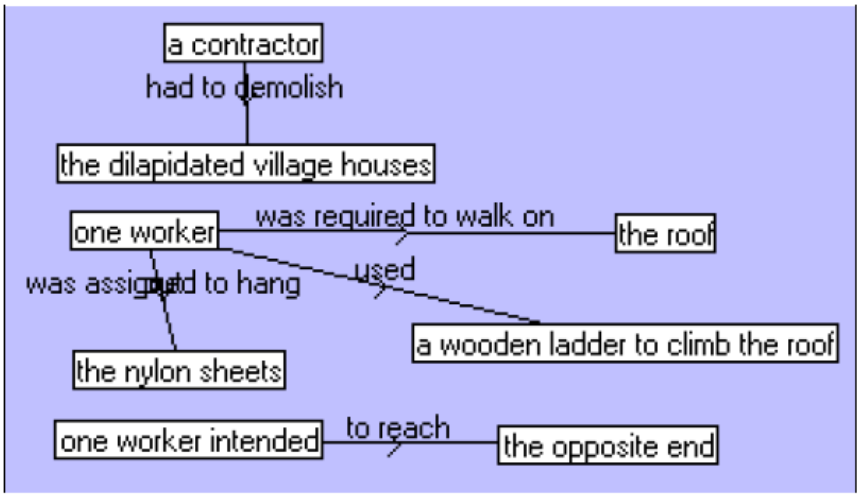


Figure D: Scenario 1-C – The detailed information about the characters in narrative map presentation

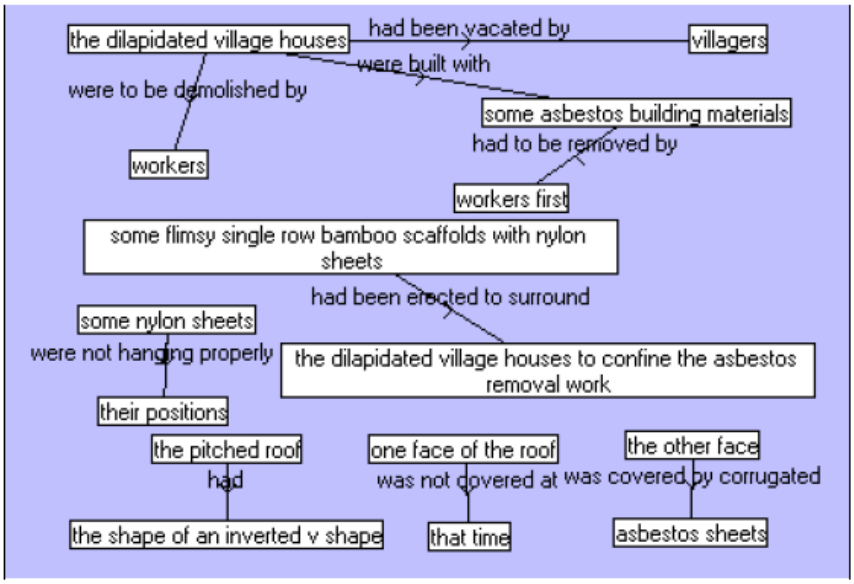


Figure E: Scenario 1-C – The detailed information about the objects in narrative map presentation

Q1-C1 With the texts provided to you, do you think that it is easy to read or understand? (Please choose one of the following.)

☐ Very easy ☐ Easy ☐ Neutral ☐ Difficult ☐ Very difficult

Q1-C2 To what extent do you agree that this way of presentation enables you to understand the texts based on people, locations, time or other concepts? (Please choose one of the following.)

☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree

Q1-C3 To what extent do you agree that this way of presentation enables you to associate relevant information from the texts? (Please choose one of the following.)

☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree

Q1-C4 To what extent do you agree that this way of presentation enables you to extract relevant information from your memory? (Please choose one of the following.)

☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree

Q1-C5 To what extent do you agree that this way of presentation enables you to learn the important issues from the texts? (Please choose one of the following.)

☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree

Q1-C6 To what extent do you agree that this way of presentation enables you to remember the important issues from the texts? (Please choose one of the following.)

☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree

Please answer question Q1-D1 based on Figures A, B, C, D and E

Q1-D1 Which presentation way will help you most to understand narratives and learn the correct lesson? (Please choose one of the following.)

☐ Scenario A ☐ Scenario B ☐ Scenario C

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Thank you for your participation.

References

Al-Humaidi, H., Tan, F., 2010. Construction Safety in Kuwait. J Perform Constr Facil. 24(1):70-77.

American Productivity and Quality Center [APQC], 2008. Retaining Today's Knowledge for Tomorrow's Work Force (Best Practices Report). http://www.apqc.org/knowledge-base/documents/retaining-todays-knowledge-tomorrows-work-force-best-practices-report (accessed 21 November, 2017).

Angeloni, S., Borgonovi, E., 2016. An ageing world and the challenges for a model of sustainable social change. J Manag D. 35(4):464-485.

Béchet, F., 2011. Named Entity Recognition. In: Gokhan T, Renato dM, editors. Spoken Language Understanding: John Wiley & Sons, Ltd. p. 257-290.

Beck, I.L., Mckeown, M.G., 1981. Developing Questions That promote Comprehension: The Story Map. Lang Arts. 58(8):913-918.

Bluck, S., Glück, J., 2004. Making Things Better and Learning a Lesson: Experiencing Wisdom Across the Lifespan. J Pers. 72(3):543-572.

Bonjour, E., Geneste, L., Bergmann, R., 2014. Enhancing experience reuse and learning. Knowledge-Based Syst. 9;68:1-3.

Burke, M.D., 2004. Use of story-mapping to increase the story-grammar text comprehension of elementary students with learning disabilities. Learn Disability Q. 27(2):105-121.

Burke, R., Kass, A., 1995. Supporting learning through active retrieval of video stories. Expert Syst Appl. 9(3):361-378.

Burnett, S., Grinnall, A., Williams, D. 2015. Knowl Manage Res Pract 13:160-167.

Center for Army Lessons Learned (CALL), 2009. Commander's Guide to Operational Records and Data Collection. http://usacac.army.mil/cac2/call/docs/09-22/ch-4.asp (accessed 8 November, 2017).

Cheuk, B., 2007. Applying sense-making and narrative techniques to capture lessons learnt, J. Infor. & Knowl. Manage., 6(3):165-171.

Choi, T.N.Y., Chan, D.W.M., Chan, A.P.C., 2012. Potential difficulties in applying the Pay for Safety Scheme (PFSS) in construction projects. Accident Anal and Prev. 48:145-155.

Coffield, F., Moseley, D., Hall, E., Ecclestone, K., 2004. Learning styles and pedagogy in post-16 learning: a systematic and critical review, LSRC reference, Learning & Skills Research Centre, London. http://lerenleren.nu/bronnen/Learning%20styles%20by%20Coffield%20e.a..pdf (assessed viewed 07 November, 2017).

Cortazzi, M., 2014. *Narrative Analysis.* Routledge.

Cunningham, H., Maynard, D., Bontcheva, K., Tablan, V., 2002. GATE: A Framework and Graphical Development Environment for Robust NLP Tools and Applications. Proceedings of the 40th Anniversary Meeting of the Association for Computational Linguistics (ACL'02) July 2002.

Derefinko, K.J., Hayden, A., Sibley, M.H., 2014. A Story Mapping Intervention to Improve Narrative Comprehension Deficits in Adolescents with ADHD, Sch Ment Health 6(4):25-2631.

Dimino, J.A., 1995, Taylor RM, Gersten RM. Synthesis of the research on story grammar as a means to increase comprehension. Read Writ Q. 11(1):53-72.

Engle, R.W., Conway, A.R.A., 1998. Working memory and comprehensive. Working memory and thinking. Logie, R.H. & Gilhooly, K.J. (Eds.) ed. East Sussex: Psychology Press. p. 67-91.

Ferrada, X., Núñez, D., Neyem, A., Serpell, A., Sepúlveda, M. 2016. A lessons-learned system for construction project management: a preliminary application. Procd Soc Behv. 226:302 – 309.

Geiger, D., Schreyögg, G., 2012. Narratives in knowledge sharing: challenging validity. J Knowl Manag. 16(1):97-113.

Geissle, C., Krys, C., 2013. The challenges of strategic management in the twenty-first century, in: Schwenker B., Wulf T. (Eds), Scenario-based Strategic Planning. Roland Berger School of Strategy and Economics, Springer Gabler, Wiesbaden, pp. 22-41.

Idol, L., 1987. Group story mapping: A comprehension strategy for both skilled and unskilled readers. J Learn Disabil, 20(4), 196-205.

Joe. C., Yoong, P., Patel, K., 2013. Knowledge loss when older experts leave knowledge-intensive organizations. J Knowl Manag. 17(6):913-927.

Kirby, J.R., Lawson, M.J., 2012. Enhancing the Quality of Learning: Dispositions, Instruction, and Learning Processes. West Nyack, NY, USA: Cambridge University Press.

Kolb, D.A., 1984. Experiential Learning: Experience as the Source of Learning and Development. Englewood Cliffs, New Jersey: Prentice-Hall.

Labor Department, 2016. Occupational safety and health statistics bulletin. http://www.labour.gov.hk/eng/osh/pdf/Bulletin2015_EN.pdf (accessed December 4, 2017).

Labov, W., Waletzky, J., 1997. Narrative Analysis: Oral Versions of Personal Experience. J Narrat Life Hist. 7(1-4):3-38.

Lawrence, R.L. and Paige, D.S. 2016. What Our Ancestors Knew: Teaching and Learning Through Storytelling. New Directions for Adult and Continuing Educ., 2016:63–72.

Marrero, M., Urbano, J., Sánchez-Cuadrado, S., Morato, J., Gómez-Berbís, J.M., 2013. Named Entity Recognition: Fallacies, challenges and opportunities. Comp Stand Inter. 35(5):482-489.

Maruta, R., 2014. The creation and management of organizational knowledge. Knowledge-Based Syst. 67:26-34.

McKinsey Quarterly, 2007. The organizational challenges of global trends: A McKinsey Global Survey. http://download.mckinseyquarterly.com/organizational_challenges.pdf (accessed 22 November, 2017).

National Aeronautics and Space Administration (NASA), 2002. NASA Better Mechanisms Needed for Sharing Lessons Learned. http://www.gao.gov/new.items/d02195.pdf. (accessed 28 November, 2017)

Özyıldırım, I., 2009. Narrative analysis: An analysis of oral and written strategies in personal experience narratives. J Pragmatics. 41(6):1209-1222.

Phelps, J.M., Strype, J., Le Bellu, S., Lahlou, S., Aandal, J., 2016. Experiential Learning and Simulation-Based Training in Norwegian Police Education: Examining Body-Worn Video as a Tool to Encourage Reflection, Policing. A J Policy and Pract, paw014.

Rupčić, N., 2017. Intergenerational learning and knowledge transfer – challenges and opportunities. Learn. Org.

Schmid, H., 1994. Probabilistic part-of-speech tagging using decision trees. In Proceedings of the international conference on new methods in language processing, Manchester, UK (pp. 44–49).

Sharma, R.S., Bhattacharya, S., 2013. Knowledge dilemmas within organizations: Resolutions from game theory. Knowledge-Based Syst. 45:100-113.

Shi, L., 2012. Ontology-based semantic reminiscence support system Cardiff School of Engineering, Cardiff University.

Snowden, D., 2002. Narrative patterns: uses of story in the third age of knowledge management, J. of Inf. & Knowl. Manage., 1(1):1-6.

Spender, J.C., 1996. Organizational knowledge, learning and memory: three concepts in search of a theory. J Organ Change Manage. 9(1):63-78.

Štajner, T., Mladenić, D., 2009. Entity Resolution in Texts Using Statistical Learning and Ontologies. In: Gómez-Pérez A, Yu Y, Ding Y, editors. The Semantic Web Heidelberg: Springer Berlin. p. 91-104.

Stringfield, S.G., Luscre, D., Gast, D.L., 2011. Effects of a Story Map on Accelerated Reader Postreading Test Scores in Students With High-Functioning Autism. Focus Autism Other Dev Disabl. 26(4):218-229.

Sumbal, M.S., Tsui, E., See-to, E., Barendrecht, A., 2017. Knowledge retention and aging workforce in the oil and gas industry: a multi perspective study, J Knowl. Manag. 21(4):907-924

Tappan, M.B., Brown, L.M., 1989. Stories Told and Lessons Learned: Toward a Narrative Approach to Moral Development and Moral Education. Harvard Educ Rev. 59(2):182-206.

Taylor, M., 2015. Skilled workers are desperately needed http://www.cpjobs.com/hk/article/growing-demand-for-skilled-workers-hong-kong%E2%80%99s-major-construction-projects (accessed December 25, 2017).

Toossi, M., 2004. Labor force projections to 2012: the graying of the U.S. workforce, Monthly Labor Review. http://www.bls.gov/opub/mlr/2004/02/art3full.pdf; (accessed 20 November, 2017).

Toossi, M. 2015. Labor force projections to 2024: the labor force is growing, but slowly, Monthly Labor Review. https://www.bls.gov/opub/mlr/2015/article/labor-force-projections-to-2024-2.htm (accessed 31 December, 2017).

Vosniadou, S., Brewer, W.F., 1992. Mental models of the earth: A study of conceptual change in childhood. Cognit Psychol. 24(4):535-585.

Weber, R., Aha, D.W., Becerra-Fernandez, I, 2001. Intelligent lessons learned systems. Expert Syst Appl. 1;20(1):17-34.

Yeung, C.L., Cheung, C.F., Wang, W.M., Tsui, E., 2014. A knowledge extraction and representation system for narrative analysis in the construction industry. Expert Syst Appl. 41(13):5710-5722.