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A Computational Narrative Simulation System For Constructing Multi-linear Narratives In Knowledge Management

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ABSTRACT:

Management of narrative is an important but difficult task. This paper presents a computational narrative simulation system (CNSS) which is developed by incorporating narrative analysis, story generation and knowledge-based systems (KBS). It aims at managing narrative knowledge systemically and constructing narrative simulation in a multi-linear form automatically. Compare to conventional methods, CNSS provides not only an important means for maintaining the story database so that an organization is able to manage narrative knowledge in a systemic manner. But also, CNSS automatically constructs new scenarios based on multiple narrative resources with multiple branches. To evaluate the performance of the system, a prototype has been built and trial implemented in a social service company in Hong Kong. The results showed that the automatic generation of multi-linear narrative is effective and the participants of the system agree that the system can improve their work.

Keywords: *Computational simulation, AI, Knowledge-based system, Knowledge management, Narrative generation*

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1. Introduction

People make sense of their lives with narratives, which plays a major role in each individual's identification of self (Kerby, 1991). According to Bruner (1991), people also organize their experience and knowing in the form of narrative. Narratives foster learning since they are rememberable, easy to understand and stimulate imagination (Lämsä and Sintonen, 2006). People can have a more comprehensible understanding on their difficulties and challenges by listening to the similar stories from others. These stories help them to adapt to the experience and discover new innovative ideas from others in order to solve their own problems (Bruner, 1991; Polkinghorne, 1988; Ricoeur, 1991).

In organizational perspective, organizational theorists have now become much aware that learning in organizations takes place through narrative knowledge. By collecting stories in a particular organization, by listening and comparing different stories, people gain access to deeper organizational realities, and closely linked to their members' experience. In recent years, numerous consultants have turned narratives as vehicles for enhancing organizational communication, performance and learning, as well as the management of change (Lämsä and Sintonen, 2006).

In particular, some researchers integrate narrative with simulation and develop the narrative simulation approach. Cole (1997) noted that each story segment presents a probable scenario that requires a series of judgments among alternative actions and provides immediate feedback about the consequences and correctness of the actions selected. Narrative simulations have been found very effective in the education of health behavior (e.g. Cole, 1997), mine safety (e.g. Cole et al, 1998) and agricultural safety (e.g. Morgan et al, 2002).

However, the data acquisition and construction of narrative simulation are labor intensive and time consuming processes. Most data acquisition methods are manually operated such as expert feedback, exercise field tests, individual and focus group interviews, observation, etc. It may take several months or even years to develop a narrative simulation Organizations require up-to-date knowledge to be easily accessed and managed in order to deal with complex, diverse and continuously evolving business environment. Furthermore, the quality of construction of narrative simulation is heavily relied on the experience of the simulation designer. It is inadequate to cope with this fast moving world in which knowledge within organizations is changing rapidly.

On the other hand, there is another stream led by David Snowden. Snowden (2000) mentions that it is now entering a new age of knowledge management, in which there is a new focus on the management of narrative. He states that it is easier, more natural and less onerous to capture narratives than written knowledge. He proposed that narrative databases can be constructed and critically indexed for decision support (Snowden, 2000). The narrative database approach provides an efficient and effective way for managing narratives in organizations. However, the application of the narrative are only focused on navigating and indexing past narratives.

This paper presents a computational narrative simulation system (CNSS) which integrates the narrative database approach and narrative simulation approach. The proposed system incorporates the current technologies used in narrative analysis and story generation, which converts multiple narratives into a multi-linear narrative. The term multi-linear narrative is used in this paper to define a form of multiple linear narratives from a highly structured collection of small narrative pieces. These narrative pieces on their own do not constitute a single narrative path or plotline, but instead they act as building blocks for constructing many different narratives. This type of story defines a form which transcends linear in the sense that it is a form from which many linear stories can be made. Figure 1 shows the structures of traditional narrative structure and multi-linear narrative structure. Multiple branches can be applied at each decision point of the narrative simulation (where decisions or actions need to be made), so that the plot of the story can be changed based on different decisions made by narrative simulation users. This provides richer information than just using a single story.

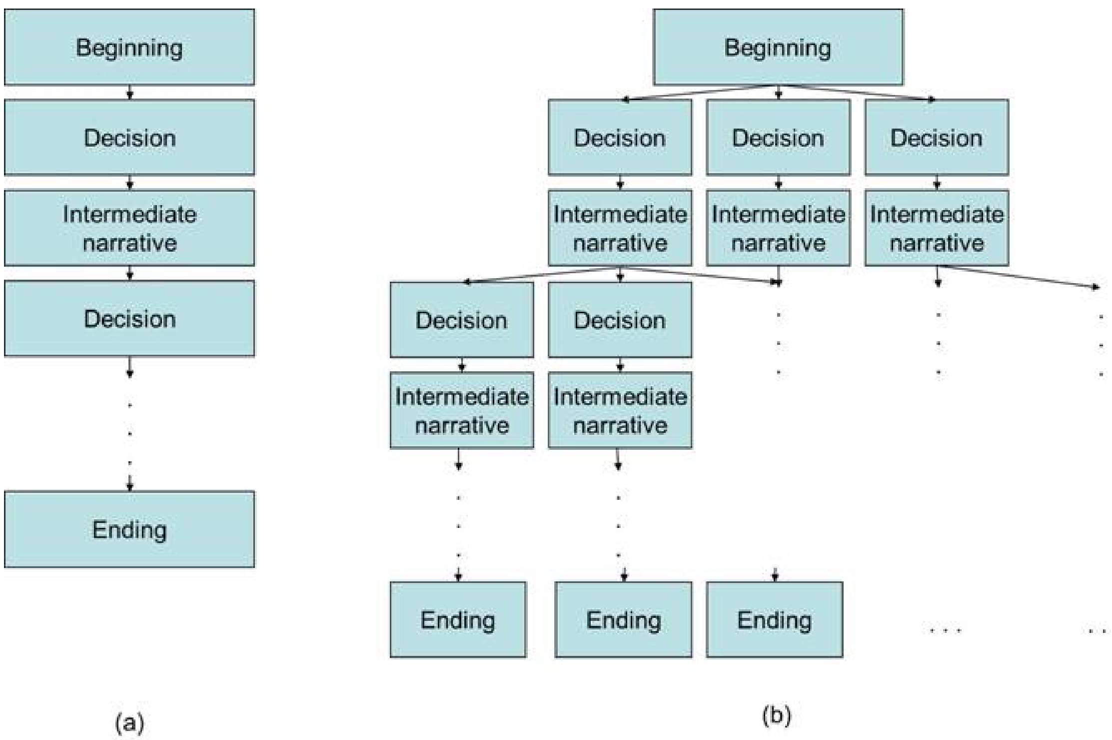

Figure 1: Traditional Narrative Structure (A) And Multi-Linear Narrative Structure (B)

2. Story Generation

Generation of narrative can be classified into two categories: manual and automatic. In manual modeling, users usually collect stories through interviews, focus group, participant observations and then aggregated into a single narrative based on their knowledge. Although manual modeling can provide users with the most accurate and complicated models, it is terribly time consuming and the quality is heavily relied on the experience of the narrative designers.

Automatic modeling only requires several input parameters to generate narratives. Early systems included TALE-SPIN (Meehan, 1977) and UNIVERSE (Lebowitz, 1985), which produce new stories by changing the initial conditions or story grammars. However, they were only able to generate a limited range of stories within a rigid pre-defined structure of the stories. Some researchers have employed story-grammars to produce automatic storytellers such as GESTER (Pemberton 1989) and JOSEPH (Lang 1997). Story grammars were developed with the objective of creating a theory of story understanding. They represent stories as linguistic objects which have a constituent structure that can be represented by a grammar (e.g. Lakoff 1972, Rumelhart 1975, Mandler and Johnson 1977). However, such kind of systems was only able to produce stories that satisfy its grammar and is not able to modify its knowledge to generate different outcomes. Some other systems such as MINSTREL (Turner, 1993; Turner, 1994), MEXICA (Pérez, 1999; Pérez et al., 2001) and BRUTUS (Bringsjord and Ferrucci 2000) are hybrid systems which consist of integrating different known methodologies into one program.

Recently, more researchers have applied ontology for the generation of narrative. MAKEBELIEVE (Liu and Singh, 2002) is an interactive story generation agent that uses commonsense knowledge to generate short fictional texts from an initial seed story step supplied by the user. The commonsense knowledge is selected from the ontology of the Open Mind Commonsense Knowledge Base (Singh, 2002). Binary causal relations are extracted from these sentences and stored as crude trans-frames. By performing fuzzy, creativity-driven inference over these frames, creative "causal chains" are produced for use in story generation. Another system named ProtoPropp which applied ontology of explicitly declared relevant knowledge and case-based reasoning (CBR) process over a case base of tales for automatic story generation that reuses existing stories to produce a new story that matches a given user query (Gervás et al, 2005). A recent model, FABULIST (Riedl et al, 2010) was an architecture for automating the processes for story generation and presentation. By given a description of an initial state of the world and a specific goal, the Fabulist identifies the optimal sequence of actions to reach the goal. They rely on detailed descriptions of the preconditions and post conditions of all the possible actions.

To summarize, the previous research work consists of predefined conditions, predefined goals, and inferred post-conditions. It requires large amount of workload for collecting, constructing and maintaining the predefined elements. The resulted narratives are also limited based on the predefined rules, and hence, the resulted narratives are rigid and lack of diversification.

3. The Computational Narrative Simulation System (CNSS)

For the CNSS, a bottom-up and semi-automatic approach was developed for collecting organizational narratives which helps to save the time and reduces the cost of knowledge update. The model converts unstructured narratives into a structured representation for abstraction and facilitating computing processing. By adapting intelligent inference algorithms, decisions and intermediate narratives are generated, so as to achieve the multi-linear narrative structure.

As shown in Figure 2, the proposed system can be divided into three parts, which are narrative collection and conversion, construction of multi-linear narrative background, and construction of decisions and consequences.

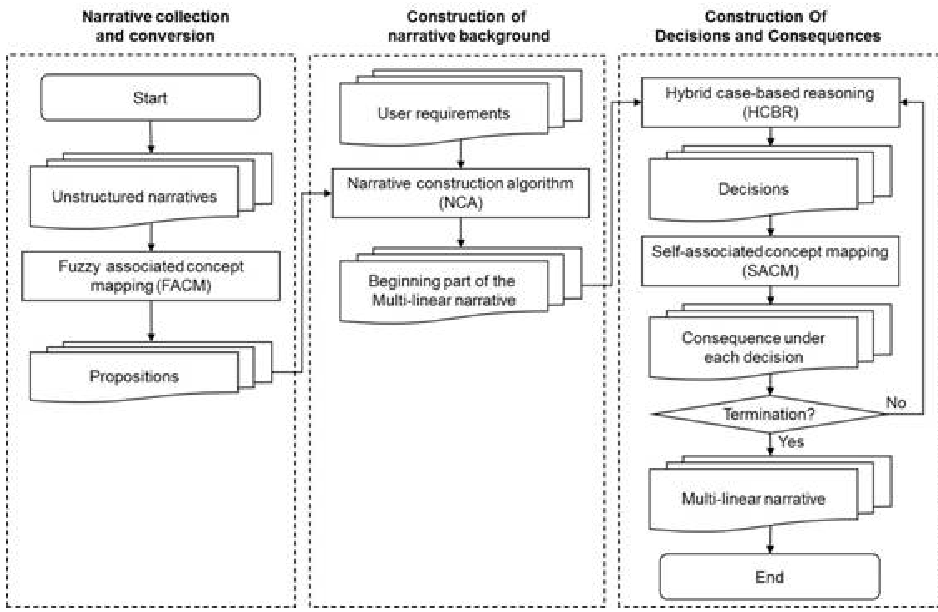

Figure 2: The Multi-Linear Construction Process

3.1. Narrative Collection And Conversion

The construction of multi-linear narrative starts with the codification of working cases during the workers' daily operation. The format of the new case is business oriented. It could be an enquiry, customer information, or a transaction, etc. Most cases consist of structured parts and unstructured parts. The structured parts consist of quantitative parameters, or optional items which have a range of well defined choices from which the worker may make a selection. The unstructured parts consist of narratives. Figure 3 depicts an example of the structured and unstructured parts of a mental health care case. The structured parts include date of assessment, father relation with the client (e.g. good, fair, and bad), etc. The unstructured parts include psychosocial history, intervention plan of the social worker, etc.

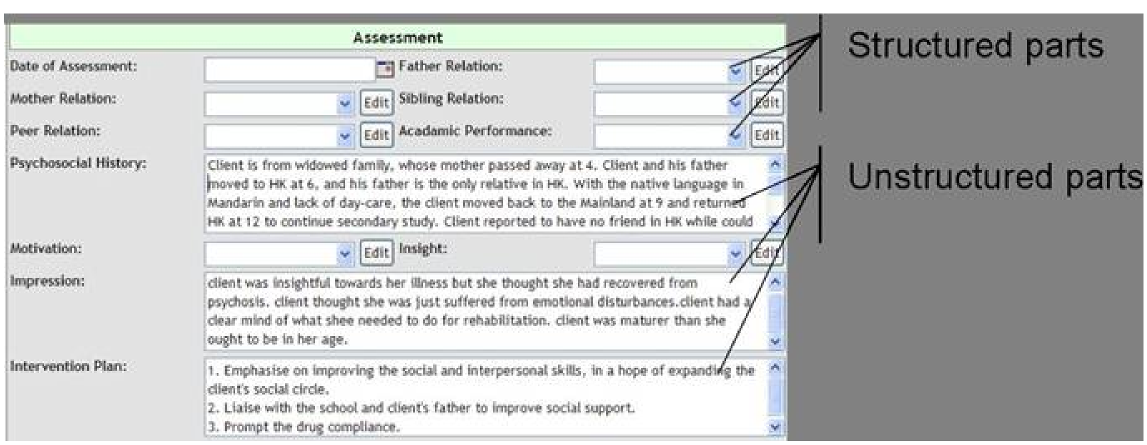

Figure 3: The Structured And Unstructured Parts Of A Case

The unstructured parts are converted into a structured format based on a Fuzzy associated concept mapping (FACM) algorithm (Wang, et al, 2008b). Each text is converted into a concept map. An example of concept map is shown in Figure 4. Each concept pairs is a proposition. As shown in Figure 4, there are 7 propositions, such as "client – have – impairment of functioning", "client – have – depressive symptoms”, etc. Hence, the information of cases together with the resulted concept maps is stored into the knowledge repository.

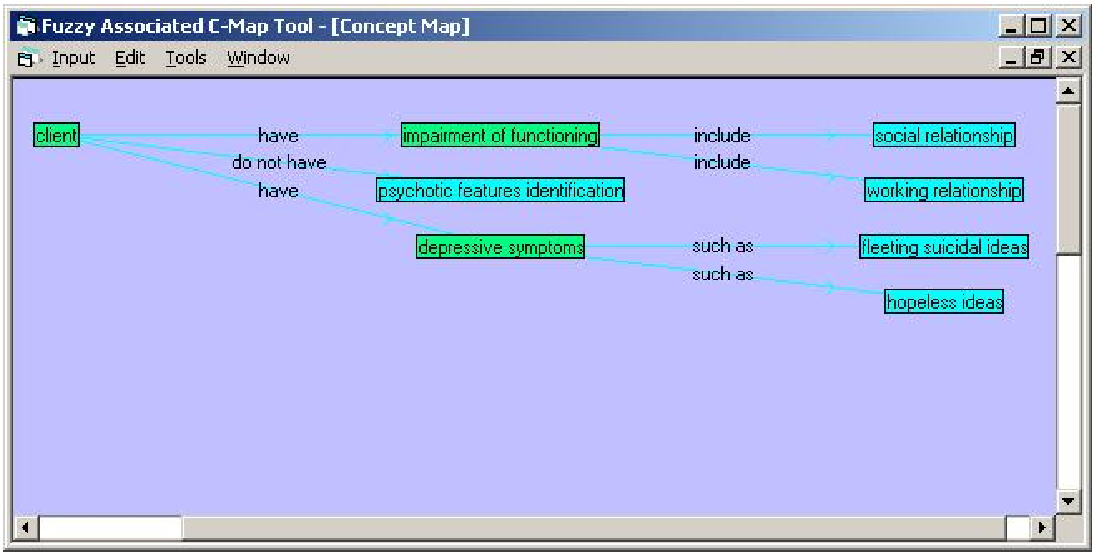

Figure 4: An Example Of Concept Map

3.2. Construction Of Background Of A Multi-Linear Narrative

As discussed in Section 1, multi-linear narrative consists of a beginning (background), and multiple decisions and consequences. The construction of a background is performed by a narrative construction algorithm (NCA) (Wang et al, 2009). Multiple texts of background information are converted into a single background automatically. A schematic diagram of the NCA is depicted in Figure 5. Based on an adaptive time series forecasting method (Wang et al, 2009), the expected length of the resultant background is determined and a list of weighted propositions is sorted by the expected values of propositions. For example, it is assumed that the expected length of resultant narrative is 2, and the top listed 3 propositions are “client’s academic performance was above average”, “client’s academic performance was below average”, and “client was diagnosed with psychosis”, respectively. Based on the conflict resolution of NCA, the 1st and 2nd propositions are contradicted with each other, and the 1st and 3rd propositions are not contradicted. As a result, “client’s academic performance was above average” and “client was diagnosed with psychosis” are selected as the resultant background.

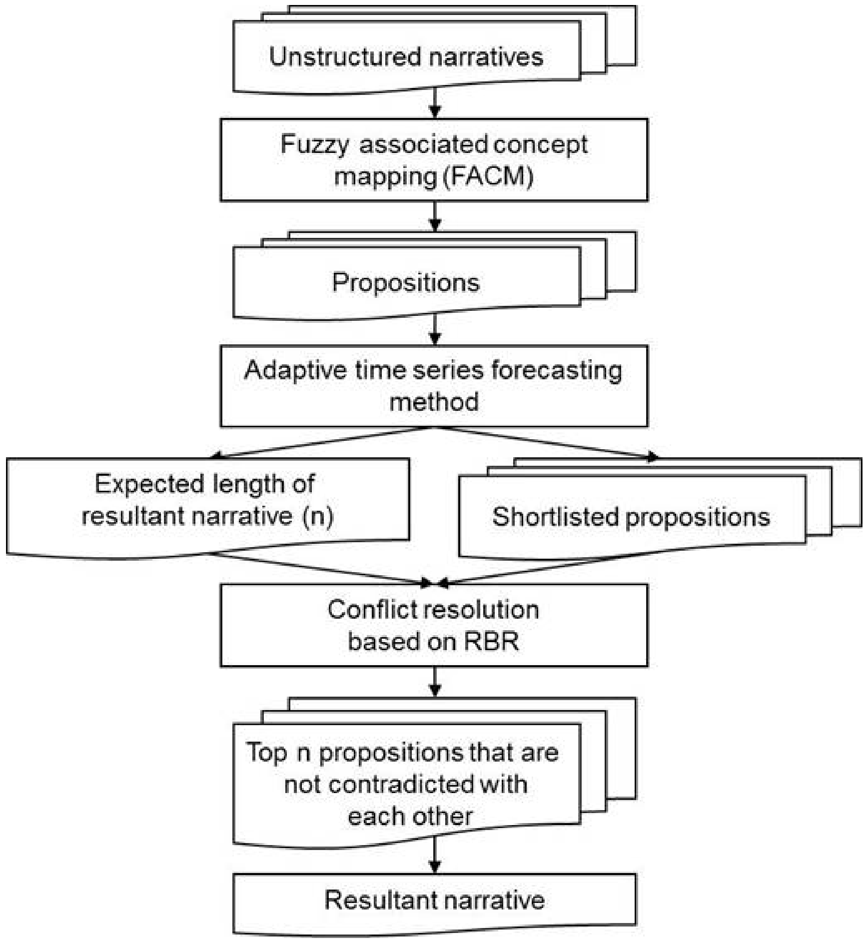

Figure 5: An Illustrative Example Of The NCA

3.3. Construction Of Decisions and Consequences

A schematic diagram of construction of decisions and consequences is shown in Figure 6. After the construction of the background of the multi-linear narrative, an inference engine, Proposition-Based Hybrid Case-based Reasoning (PB-HCBR), is applied to infer the decision choices. Then, another inference engine named proposition-based Self associated concept map (PB-SACM) is used to associate the relevant concepts related to the inferred decision choice. The associated concepts are then consolidated to formulate an intermediate narrative. If the intermediate narrative is not determined as an ending of the multi-linear narrative, the PB-HCBR is applied again for the inference of decision choices. The loops go on until all decision choices have endings.

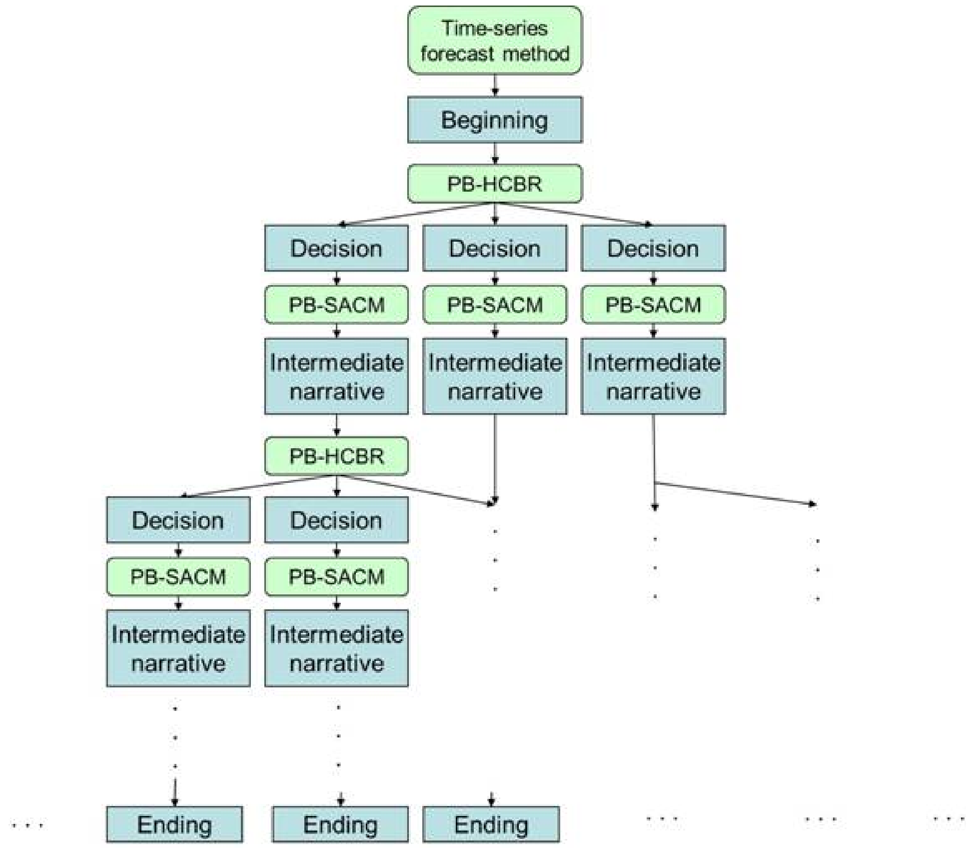

Figure 6: A Schematic Diagram Of The Decisions And Consequences Construction

PB-HCBR is adapted from hybrid case-based reasoning (HCBR) that presented in Wang, et al (2007). HCBR was an intelligent inference algorithm by combining aspects of case-based reasoning (CBR), rule-based reasoning (RBR) and fuzzy theory based on structured data. In this paper, it is adapted for deducing the decisions of a multi-linear narrative based on unstructured narrative data. As shown in Figure 7, PB-HCBR is composed of three main parts which include CBR, RBR and combination of CBR and RBR, respectively.

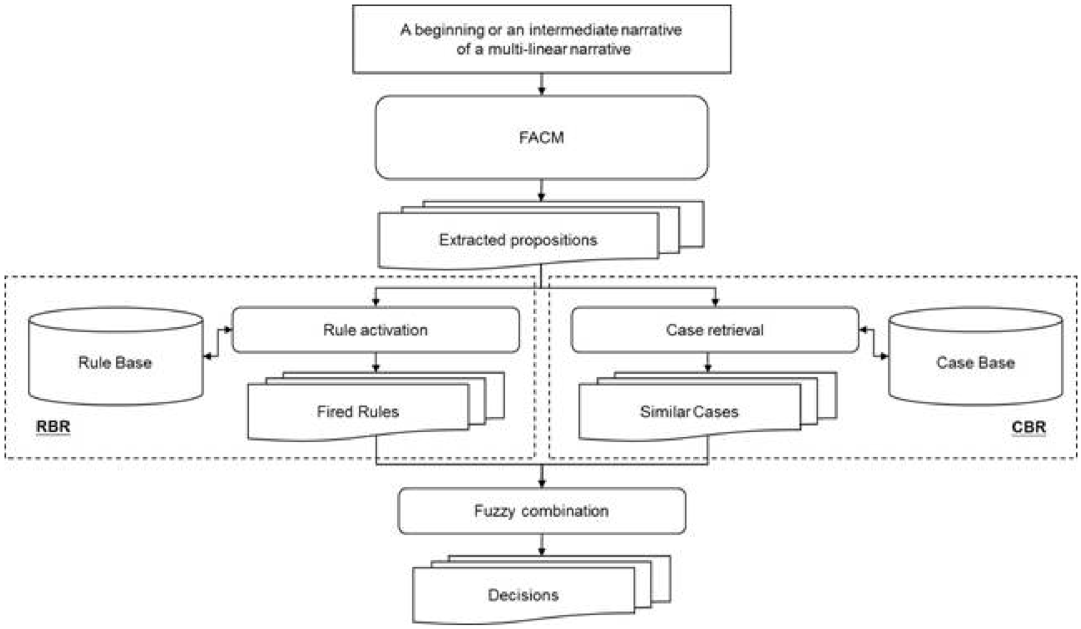

Figure 7: The Schematic Diagram Of Proposition-Based Hybrid Case-Based Reasoning

In the CBR part, a similarity measure calculates the similarity between the input propositions and the propositions of the backgrounds or reviews of previous cases that are stored in the case base. The RBR part consists of a rule base and an inference engine. The results of CBR and RBR are then combined as the decisions. An illustrative example of PB-HCBR is shown in Figure 8. It is assumed that there is a background with 3 propositions (i.e. P1, P2, and P3). Based on CBR, the similarities between the background and previous cases are determined. The decision of the most similar case is then extracted (i.e. D1). On the other hand, a rule is fired based on matching the rule base in RBR and the decision of the rule is extracted (i.e. D2). The results are then combined (i.e. D1 and D2).

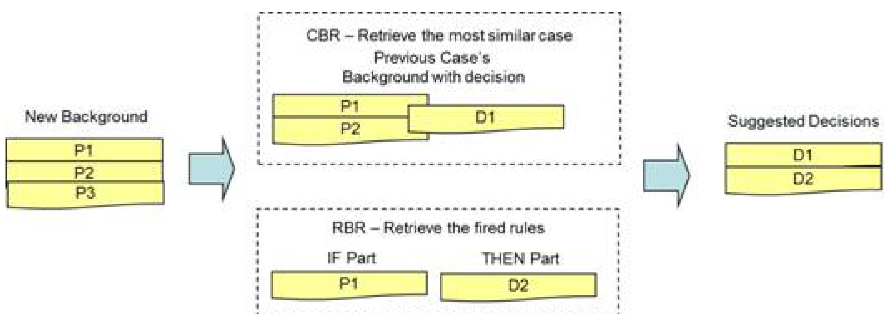

Figure 8: An Illustrative Example Of PB-HCBR

After the generations of decision choices by PB-HCBR, PB-SACM serves as an inference engine for deducing the intermediate narrative under each decision choice. PB-SACM is proposed by adapting self-association concept mapping (SACM) that developed in Wang, et al (2008a). SACM extends the use of concept mapping by proposing the idea of self-construction and automatic problem solving based on structured historical records. PB-SACM is being adapted to infer intermediate narratives based on unstructured narrative data.

The adoption of PB-SACM involves two phrases: learning phase and application phase. In the learning phase as shown in Figure 9, the background narratives, decisions and intermediate narratives are converted into proposition by FACM and then they are aggregated into a PB-SACM format. A PB-SACM is defined with all necessary notations as follows:

Let $K=[0,1]$, a PB-SACM is a 4-tuple $(\boldsymbol{C},\boldsymbol{F},\boldsymbol{L},\boldsymbol{P})$ where $\boldsymbol{C}=(C_1,C_2,\ldots,C_n)$ is a set of n distinct proposition forming the nodes of a PB-SACM, $\boldsymbol{F}=(F_1,F_2,\ldots,F_n)$ is a function that at each C_i associates its degree of importance F_i with $F_i \in K$, $\boldsymbol{L}:(C_i,C_j)\rightarrow L_{ij}$ is a function that a pair of proposition (C_i,C_j) associates its degree of importance L_{ij}, with L_{ij} denoting a weighting of directed edge from C_i to C_j, $L_{ij}\in K$ if $i\neq j$, and $L_{ij}=0$ if $i=j$, $\boldsymbol{L}$ represents a set of degree of association between all concepts in a PB-SACM, $\boldsymbol{P}=(F_{max},L_{max},N)$ is a set of parameter which facilitates the inference, with F_{max} and L_{max} indicate the maximum value of $\boldsymbol{F}$ and $\boldsymbol{L}$ before normalization respectively, and N indicates the total number of records that have been assimilated to this PB-SACM.

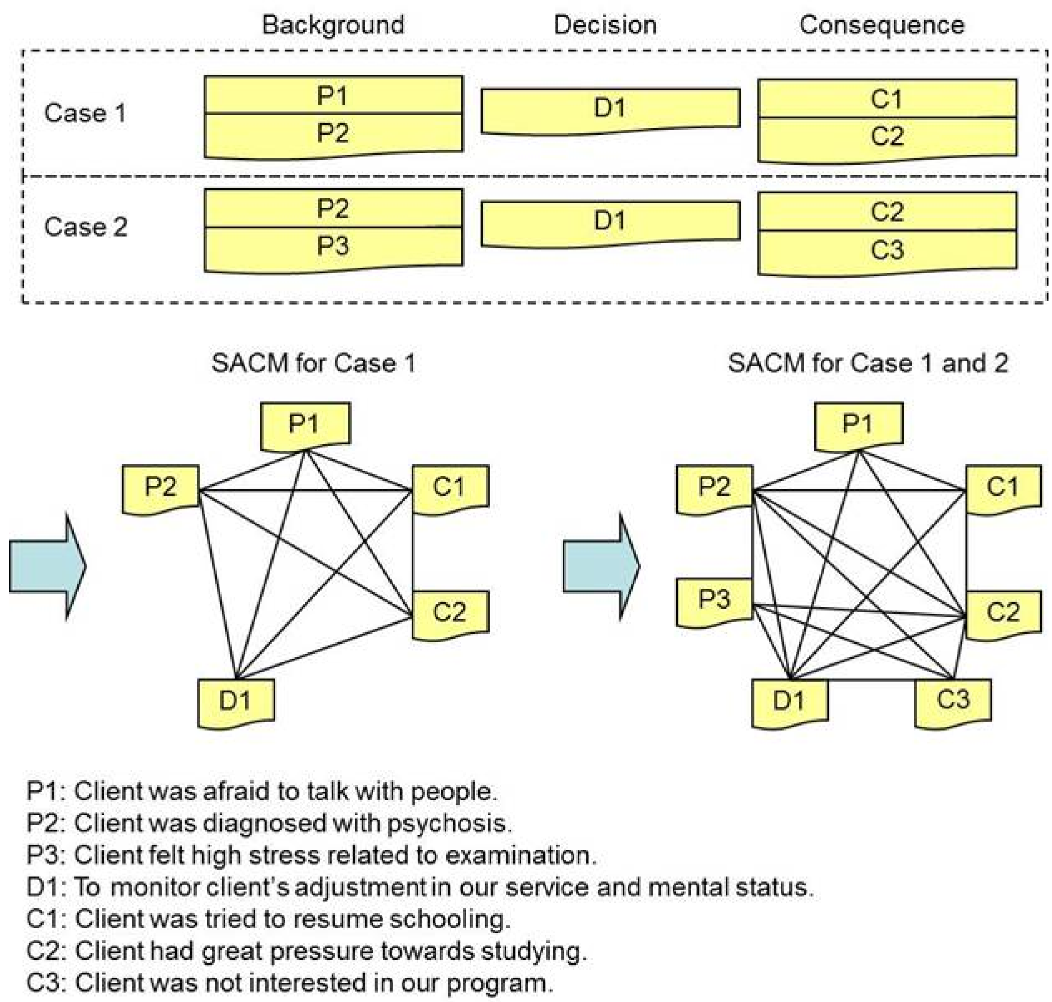

Figure 9: An Illustrative Example Of Learning Phase Of PB-SACM

In the application phase, the background narrative (constructed by NCA) and decision (constructed by PB-HCBR) are converted into PB-SACM format. The activation level of each node of the PB-SACM is then computed. The activated nodes are then combined as the intermediate narrative of the multi-linear narrative. Following the example in Figure 9, an illustrative example of PB-SACM application phase is shown in Figure 10. The propositions of a background narrative (P1 and P3) and decision (D1) are matched with the PB-SACM trained in the learning phase. For example, the propositions C1, C2 and C3 are activated. Based on filtering by a predefined threshold, only C2 is left as the intermediate narrative.

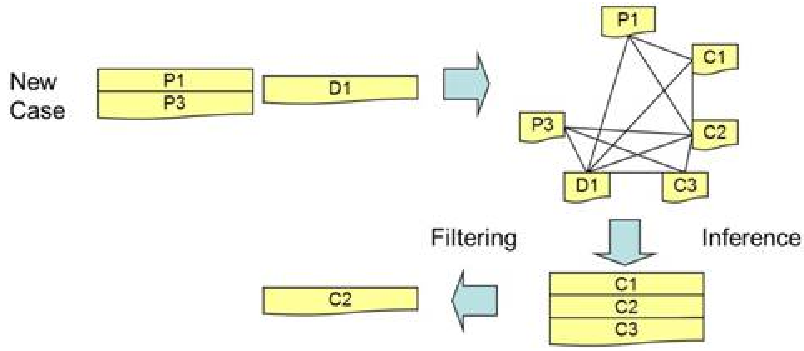

Figure 10: An Illustrative Example Of Application Phase Of PB-SACM

4. Experimental Verification

There are two experiments have been carried out for evaluating the proposed system. The first experiment aims to measure the usability of the proposed system through a trial implemented in a Department of a social service organization in Hong Kong. The selected Department is responsible for providing early intervention with mental healthcare care services for adolescents. It has implemented a workflow management system for managing the case information. Each case contains both structured and unstructured information. This includes the personal data, mental health assessment, development history, suicidal history, family background, treatment records, review records, etc.

During the caring process, social workers interview clients and carry out diagnostic assessment for evaluating mental health status of the clients. The social worker is required to write a small narrative into the system to describe the problem of the client. Based on the presented problem, the social worker derives the treatment plan and helps the client to establish the determined goals. Until the client's condition is satisfied, the case will be reviewed periodically to evaluate the progress and adjust the treatment plan.

In this paper, 72 cases are collected. The cases are first analyzed by the FACM which converts the narratives into a structured data format. The information of mental health assessment, development history, suicidal history, and family background is used and analyzed by NCA, which constructs the beginning of the multi-linear narrative. The treatment records and review records are used to deduce the decisions and intermediate narratives, which are analyzed by the PB-HCBR and PB-SACM algorithms. Finally, the termination records are used to check the ending of the output narrative. Figure 11 shows a screenshot of the resulted beginning of the output narrative. The output narrative consists of 6 levels, 40 narrative segments, and 39 decisions.

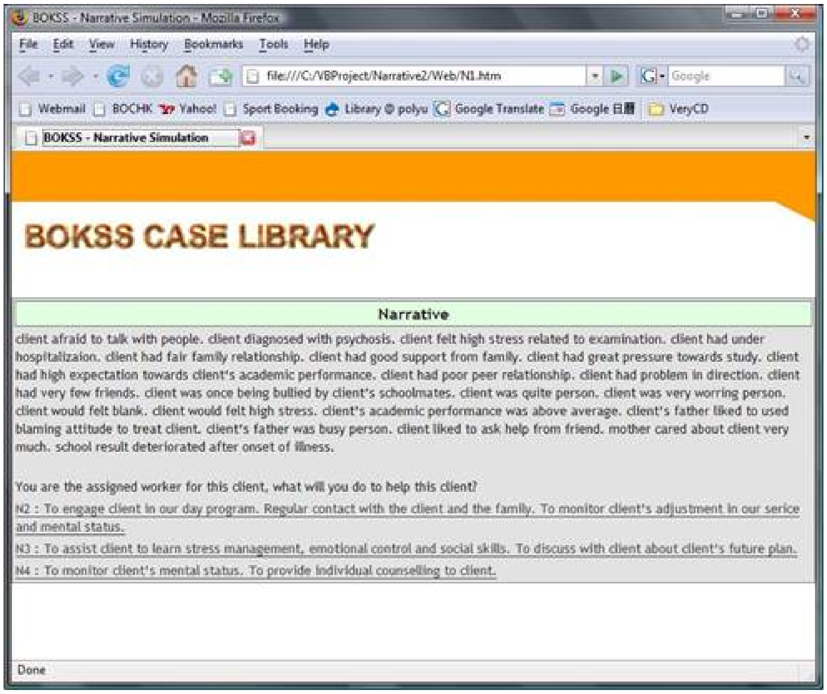

Figure 11: A Screenshot Of Beginning Of The Narrative Simulation

The field test of the narrative simulation was conducted with the case workers of the organization and students of social work. 17 participants were involved in the experiment. By adapting the narrative simulation evaluation proposed by (McCrary and Mazur, 1999), ten questions were set and they were rated from 1 to 5 (5 is highest agreement) on a Likert scale. The findings are summarized and reported in terms of general agreement with specific evaluation questions as indicated by user choice of either number (4) or (5) on the scale, disagreement by choice of number (1) or (2), and neutral by choice of number (3). The evaluation questions are categorized into different areas which include veracity, informative, cognitive, usability and affective. Table 1 summarizes the participant evaluations and includes the percentage results.

Two evaluation items are related to veracity which specify the truth-likeness of the narrative. Although participants were told that this exercise was formulated on true stories, their perceptions on believing in the reality of the narrative were important. As a result, one statement stated that the story was realistic, while the other concerned the extent to which the users could relate personally to the story. By excluding the neutrals, more people indicated that they could relate personally and more participants agreed that the story was realistic. There was one evaluation statement regarding the informative nature of the simulation. 64.7% of participants agreed that the simulation was informative. There were two statements designed to get a sense of whether participants felt that they have learnt something new and they could remember important things from the exercise. By excluding the neutrals, more people believed they had learned something new and 50% of the participants indicated that the exercise helped them to remember important things.

Table 1: User Evaluation Results Of The Output Narrative (n = 17)

Evaluation Questions	Design Category	Agree	Disagree	Neutral
The exercise is realistic and authentic.	Veracity	41.2%	11.8%	47.1%
I can relate personally to the exercise.	Veracity	41.2%	11.8%	47.1%
The content is informative.	Informative	64.7%	11.8%	23.5%
I learned something new from the exercise.	Cognitive	29.4%	5.9%	64.7%
It helped me remember important things	Cognitive	35.3%	35.3%	29.4%

The length of exercise is appropriate	Usability	70.6%	5.9%	23.5%
The exercise is easy to understand	Usability	64.7%	17.6%	17.6%
The exercise is interesting	Affective	41.2%	35.3%	23.5%
The exercise made me feel uncomfortable	Affective	17.6%	23.5%	58.9%
Overall, the exercise is useful	Overall	29.4%	52.9%	17.6%

Two specific statements in the evaluation related to the usability of the simulation. Those were statements regarding the length of the simulation, and the ease of understanding. 70.6% of users indicated that the length was appropriate. 64.7% of participants agree that the simulation was easy to understand. Two statements intended to understand the extent to which this experience was interesting and made participants feel uncomfortable. The results showed that 17.6% of users felt the exercise was interesting with 23.5% disagreeing. 29.4% of participants felt uncomfortable and 52.9% did not feel uncomfortable. As a whole, 23.5% of users agreed that the system can improve their work and that the exercise was useful with 5.9% disagreeing.

The second experiment was carried out to evaluate the effectiveness of the system by measuring the learning outcome of the users after using the system. The participants were divided into 2 groups which included an experiment group (8 participants) and a control group (5 participants). The members of the experimental group participated in the narrative simulation, and then they were evaluated through a testing exercise. The participants of the control group were directly evaluated by the testing exercise, without participated in the narrative simulation. The questions of the testing exercise were randomly selected from the cases of the knowledge base of the system and the answer choices were generated based on the similarity analysis. The selected cases were excluded from the cases used for building the narrative simulation in order to prevent the direct matching between the narrative simulation and the test. The testing exercise was composed of 10 multiple choices questions.

As shown in Table 2, the average mark of the experimental group was 17% higher than that of the control group, which inferred that the system can significantly improve their work. A student's t-test is also conducted to compare the result of control group and experiment group. As shown in Table 3, the averaged accuracy of experiment group was significantly higher than the averaged accuracy of control group ($p=0.04$). On the whole, the CNSS has successfully been implemented in the reference site. The performance of the system in real life application is found to be good which are substantiated by the encouraging results obtained.

Table 2: Results Of Learning Outcome Of The Users

Question	**Averaged accuracy of control group**	**Averaged accuracy of experiment group**
Q1	0%	25%
Q2	20%	25%
Q3	60%	87.5%
Q4	40%	87.5%
Q5	40%	37.5%
Q6	20%	25%
Q7	60%	25%
Q8	40%	50%
Q9	40%	62.5%
Q10	20%	87.5%
Q1 to Q10	34%	51.25%

Table 3: t-Test: Paired Two Sample for Means

	Averaged accuracy of control group	**Averaged accuracy of experiment group**
Mean	0.34	0.5125
Variance	0.036	0.077951389

Observations	10	10
Pearson Correlation	0.330350425	
Hypothesized Mean Difference	0	
df	9	
t Stat	-1.941374014	
P(T<=t) one-tail	0.042061817	
t Critical one-tail	1.833112923	
P(T<=t) two-tail	0.084123635	
t Critical two-tail	2.262157158	

5. Conclusion

In this paper, a computational narrative simulation system is presented by incorporating the knowledge-based systems (KBS) and artificial intelligence (AI) technologies, which aims at converting multiple narratives into a multi-linear narrative. The model offers a dynamic and customizable construction of narrative simulation. The method adopts a semi-automatic method to convert workers' narratives into structured format and automatically constructing a multi-linear narrative based on the converted narratives. The automatic process facilitates the collection and conversion of narratives, and the time and efforts for a narrative construction can be dramatically reduced so that less experienced narrative designer can be employed.

Experimental evaluations were carried out by trial implementation of the computational narrative simulation system in a social service company in Hong Kong. A survey was distributed for measuring the performance of the constructed narrative. The results shows that majority of the participants agree that the narrative is informative, realistic and authentic. Participants can relate personally to the narrative and they have learnt something new from the narrative. Participants agree that the length of narrative is appropriate, and the narrative is easy to understand and answer. On the whole, they expressed that the exercise is useful. Another experiment was also carried out to measure the learning outcome of the participants. The results show that the averaged marks of experiment group were 17% higher than that of the control group. This infers that the system can improve their work. Moreover, the automatic transformation of multiple narrative data into a multi-linear narrative achieved the desired design intentions. Future work will be done on enhancing the group discussion during the narrative simulation. Moreover, the computational narrative simulation will be applied to different knowledge domains for testing and evaluation.

6. Acknowledgements

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