Copyright Undertaking

This thesis is protected by copyright, with all rights reserved.

By reading and using the thesis, the reader understands and agrees to the following terms:

1. The reader will abide by the rules and legal ordinances governing copyright regarding the use of the thesis.

2. The reader will use the thesis for the purpose of research or private study only and not for distribution or further reproduction or any other purpose.

3. The reader agrees to indemnify and hold the University harmless from and against any loss, damage, cost, liability or expenses arising from copyright infringement or unauthorized usage.

If you have reasons to believe that any materials in this thesis are deemed not suitable to be distributed in this form, or a copyright owner having difficulty with the material being included in our database, please contact lbsys@polyu.edu.hk providing details. The Library will look into your claim and consider taking remedial action upon receipt of the written requests.

Pao Yue-kong Library, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

http://www.lib.polyu.edu.hk
COMPUTATIONAL NARRATIVE SIMULATION FOR ORGANIZATIONAL LEARNING

WANG Wai Ming

A thesis submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy

September, 2008
CERTIFICATION OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

___________________________
WANG Wai Ming
Organizational learning (OL) is one of the most important capabilities for the survival of an organization. Organizations need to have the dynamic capabilities to create, capture, harvest, share, replenish and apply their knowledge. Knowledge comes from experience and resides in the narratives of how people deal with real-life problems, so the acquisition of knowledge must be interwoven with the process of applying it. Knowledge workers need to have exposure to problems in order to achieve OL. However, it is difficult to acquire knowledge from narratives and difficult to share it efficiently and effectively. Traditional methods are shown to be ineffective in fulfilling the requirements of the important knowledge processes and in supporting the factors that facilitate OL.

In the present study, a Computational Narrative Simulation (CNS) approach is presented and a Computational Narrative Simulation System (CNSS) has been designed and built to overcome the limitations in the existing methods. By incorporating the technologies of knowledge-based systems (KBS) and artificial intelligence (AI), four computational intelligent algorithms have been developed for supporting the automation of the narrative simulation. These algorithms are: Fuzzy-Associated Concept Mapping (FACM), a narrative prediction and construction algorithm, Hybrid Case-based Reasoning (HCBR), and Self-Associated Concept Mapping (SACM).

The FACM was developed in order to collect unstructured narrative knowledge and convert it into structured knowledge represented in such a way that it can be
processed easily by computers. It supports the simulation designer in managing a massive quantity of narrative data collected from the workers. The narrative prediction and construction algorithm is used for selecting relevant narratives for the construction of narrative simulations. Narratives that refer to situations that will probably occur in the near future are selected for constructing the beginning of the narrative of a narrative simulation. The HCBR algorithm has been developed for deducing the decision points, questions and answer choices in the narrative simulation. A SACM algorithm has been developed which serves as an inference engine for associating the decision points with the narrative segments in the narrative simulation.

To evaluate the performance of these algorithms, a series of quantitative experiments has been carried out. The value and capability of these algorithms are realized by using various public databases and industrial data. The results are also benchmarked with well known algorithms and commercial software (e.g. ANNIE). It is interesting to note that the FACM increases the recall rate (about 40% to 50% improvement) and maintains a high precision rate (over 80%) when compared with the baseline algorithm. There is an over 70% accuracy of the narrative prediction and construction algorithm in the prediction of propositions when the time interval is set to 3 months or above. The accuracy is good, even though the accuracy of the method is calculated on a basis on strict restrictions and strict conditions. The accuracy of HCBR is higher than that of the well known algorithms known as the Case-based Reasoning (CBR) algorithm (about 12% to 22% improvement) and the Rule-based Reasoning (RBR) algorithm (about 3% to 47% improvement). For testing the SACM, two experiments were carried out. The first experiment shows that the accuracy of
SACM is compatible with the accuracy of human beings. According to the correlation analysis, SACM has a high correlation (0.90) when tested on laymen of the tested domain when compared with CBR (0.69). The knowledge inference of SACM has the advantages of higher laymen learning capability, smaller data size and faster speed, than CBR. The results of the second experiment show that the SACM and the CBR have a similar average accuracy and the accuracy of SACM increases significantly when the number of learning cases increases. Clearly, the SACM is useful and capable of simulating human learning activities. It is an important base for the development of the CNSS.

In order to evaluate the performance of the CNSS as a whole in real-life implementation, a prototype system has been built and trial implemented for case management in a social service organization (i.e. Baptist Oi Kwan Social Service (BOKSS)) organization. A survey was distributed to the case workers for measuring the performance of the narrative that was constructed by the CNSS. The results show that the participants generally agreed that the narrative was informative, realistic and authentic. The participants were able to relate personally to the narrative and they said that they had learnt something new from the narrative. They agreed that the length of narrative was appropriate, the narrative was easy to understand and the questions were easy to answer. On the whole, the participants commented that the constructed narrative was useful. A controlled experiment was also carried out for measuring the learning outcome created by the system. From the results, the average mark of the experimental group were 17% higher than that of the control group, which indicated that the system was able to improve their work.
On the whole, a novel computational narrative simulation (CNS) method has been established, which addresses the deficiencies and limitations of traditional narrative simulation approaches for achieving organizational learning (OL). It integrates a number of technologies. Such integration of technologies is considered as novel. Four computational intelligent algorithms have been developed for the realization of the CNS. Fuzzy associated concept mapping (FACM) has been developed for automatically mining concept maps from natural language texts by the novel integration of natural language processing (NLP) with concept mapping. Narrative prediction and construction has been developed based on the technologies of KBS, computational linguistics, and a forecasting method for automating the narrative construction. Hybrid case-based reasoning (HCBR) has been built by integrating case-based reasoning (CBR) and rule-based reasoning (RBR) technologies. Self-associated concept mapping (SACM) extends the use of concept mapping by proposing the idea of self-construction and automatic problem solving. A Constrained Fuzzy Spreading Activation (CFSA) model has been developed for supporting rapid and automatic decisions inference in SACM. The development of the four algorithms not only contributes to the advancement of the computational intelligent technologies in the field of the present study, but also provides an important means for supporting the building the computational narrative simulation system (CNSS).

With the successful development of the CNS methodology and hence the CNSS, an organization is capable of managing narrative knowledge in a systemic manner. The CNS makes efficient and effective use of organizational narrative knowledge and narrative simulation for achieving OL. The CNSS provides an important means
Abstract

for automatic integration of narratives with simulation. As a result, the time for construction of a narrative simulation can be dramatically reduced, and the learners can test their actions and consequences in a more cost effective, faster, appropriate, flexible, and ethical manner. The learners can recognize the choices, decisions, and experience that lead to the consequences of the decisions that have been made. With the successful implementation of the CNS, the capabilities of an organization for knowledge creation, knowledge sharing, knowledge storage, and knowledge application can be significantly enhanced.
ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to Dr. Benny Cheung, Associate Professor and Associate Director of Knowledge Management Research Centre, Department of Industrial Systems Engineering, The Hong Kong Polytechnic University for his excellent supervision and valuable advice throughout the research. Moreover, I appreciate his help, continuous guidance, motivation and encouragement at every stage of my research. I thank him for allowing me a great deal of independence.

Thanks also go to Professor W. B. Lee and Dr. S. K. Kwok for their valuable comments and advice on my research. They are always supportive and providing the research direction. I would like to thank people associated with Baptist Oi Kwan Social Service (BOKSS) organization for providing the workplace and reference site for the field work study. Many thanks are also due to their kind assistance in the system implementation and validation.

During the course of my study, I have been very fortunate to have the help and support of many friends and colleagues. I would like to thank Burly, Caroline, Elsa, George, Meina, Mike, Rick and Tracy for their thoughtful discussion and help. For supporting my research at the University, I would like to thank the financial support from the Research Committee of The Hong Kong Polytechnic University. Especially, I am truly grateful to my father, mother, and Fiona for their love and unwavering faith in me over the past many years.
# Table of Contents

## Abstract .................................................................................................................. i

## Acknowledgements ............................................................................................ vi

## Table of Contents ............................................................................................... vii

## List of Figures .................................................................................................... xi

## List of Tables ...................................................................................................... xiv

## List of Abbreviations .......................................................................................... xv

## Chapter 1 Introduction ......................................................................................... 1

1.1 Research background ...................................................................................... 1

1.2 Problem identification .................................................................................... 4

1.3 Research objectives ....................................................................................... 5

1.4 Organization of the thesis ............................................................................ 6

## Chapter 2 Literature Review ............................................................................... 8

2.1 Organizational knowledge ............................................................................... 9

2.2 Knowledge processes in organizations ......................................................... 13

2.2.1 Knowledge creation ............................................................................ 13

2.2.2 Knowledge storage and retrieval ......................................................... 17

2.2.3 Knowledge transfer and sharing ......................................................... 19

2.2.4 Knowledge application .................................................................... 19

2.3 Organizational learning and knowledge management .................................. 20

2.3.1 Overview of knowledge management (KM) .................................... 20

2.3.2 Organizational learning (OL) and its relationships to KM .......... 21

2.3.3 Facilitating factors for OL ............................................................... 26

2.4 Organizational learning approaches ............................................................ 27

2.4.1 Industrial engineering .................................................................... 28

2.4.2 On-the-job training and e-learning system ..................................... 29

2.4.3 Action research .............................................................................. 31

2.4.4 Organizational storytelling ............................................................. 33

2.4.5 Knowledge-based system (KBS) .................................................... 35

2.4.6 Narrative database ....................................................................... 37
<table>
<thead>
<tr>
<th>2.4.7</th>
<th>Computational simulation</th>
<th>39</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.4.8</td>
<td>Narrative simulation</td>
<td>47</td>
</tr>
<tr>
<td>2.4.9</td>
<td>Limitations of conventional approaches for OL</td>
<td>49</td>
</tr>
<tr>
<td>2.5</td>
<td>Technologies for OL</td>
<td>51</td>
</tr>
<tr>
<td>2.5.1</td>
<td>Automatic narrative generation</td>
<td>51</td>
</tr>
<tr>
<td>2.5.2</td>
<td>Artificial intelligence (AI)</td>
<td>57</td>
</tr>
<tr>
<td>2.5.3</td>
<td>Data mining</td>
<td>65</td>
</tr>
<tr>
<td>2.5.4</td>
<td>Concept mapping</td>
<td>70</td>
</tr>
<tr>
<td>2.6</td>
<td>Summary</td>
<td>76</td>
</tr>
</tbody>
</table>

CHAPTER 3 COMPUTATIONAL NARRATIVE SIMULATION (CNS)........ 80

| 3.1   | Research methodology     | 80 |
| 3.2   | A comparison between traditional approach and CNS approach for OL | 81 |
| 3.3   | Architecture of the computational narrative simulation system (CNSS) | 87 |
| 3.3.1 | Knowledge-based system (KBS) | 88 |
| 3.3.2 | Narrative simulation construction system (NSCS) | 90 |
| 3.3.3 | Knowledge repository    | 93 |
| 3.3.4 | Computational intelligent algorithms | 95 |
| 3.4   | Assumptions of the CNS methodology for OL | 97 |
| 3.5   | Fuzzy associated concept mapping (FACM) | 98 |
| 3.5.1 | Anaphora resolution     | 99 |
| 3.5.2 | Word normalization       | 103 |
| 3.5.3 | Graphical representation | 103 |
| 3.5.4 | Proposition recommendation | 104 |
| 3.6   | Narrative prediction and construction | 107 |
| 3.7   | Hybrid case-based reasoning (HCBR) | 112 |
| 3.7.1 | Case-based reasoning (CBR) | 112 |
| 3.7.2 | Rule-based reasoning (RBR) | 117 |
| 3.7.3 | Combination of CBR and RBR | 119 |
| 3.7.4 | An illustration of the HCBR | 121 |
| 3.8   | Self associated concept mapping (SACM) | 124 |
| 3.8.1 | Knowledge representation of the SACM | 125 |
| 3.8.2 | Knowledge elicitation of the SACM | 126 |
| 3.8.3 | Knowledge inference of the SACM | 130 |
# Table of Contents

3.8.4 An illustrative example of the SACM ........................................... 132
3.9 Summary .......................................................................................... 138

## CHAPTER 4 PERFORMANCE EVALUATION FOR THE COMPUTATIONAL INTELLIGENT ALGORITHMS

4.1 Experimental verification for the FACM .............................................. 141
4.2 Experimental verification for the narrative prediction and construction .... 147
4.3 Experimental verification for the HCBR ................................................ 156
4.4 Experimental verification for the SACM .............................................. 160
4.5 Summary .......................................................................................... 165

## CHAPTER 5 IMPLEMENTATION AND CASE STUDY

5.1 Company background ......................................................................... 168
5.2 Evaluation of the knowledge-based system (KBS) .................................. 169
5.3 Evaluation of the narrative simulation construction system (NSCS) ......... 173
5.4 Prerequisites and limitations of the case study ..................................... 179
5.5 Summary .......................................................................................... 180

## CHAPTER 6 OVERALL CONCLUSIONS

## CHAPTER 7 SUGGESTIONS FOR FUTURE WORK

7.1 Applications in other industries ......................................................... 188
7.2 Further enhancement of the capability of knowledge acquisition .......... 188
7.3 Individual and shared mental models .................................................. 189
7.4 Multimedia integration ...................................................................... 190

REFERENCES .......................................................................................... 191
PUBLICATIONS ...................................................................................... 216

APPENDIX A – PARTS-OF-SPEECH TAGSET ........................................ A1
APPENDIX B – CONCEPT ACQUISITION RULE SET ............................. A2
APPENDIX C – CONCEPT ACQUISITION CASE SET ............................... A3
APPENDIX D – NEWS ARTICLES’ LINKS .............................................. A4
APPENDIX E – USER INTERFACE OF CASE LIBRARY ....................... A5
Table of Contents

APPENDIX F – CASE LIBRARY EVALUATION QUESTIONNAIRE ........ A13
APPENDIX G – USER INTERFACE OF NARRATIVE SIMULATION....... A17
APPENDIX H – NARRATIVE SIMULATION QUESTIONNAIRE............... A23
APPENDIX I – SOURCE CODE OF NARRATIVE SIMULATION .............. A24
### LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Shifting of learning curves for individual workers</td>
<td>2</td>
</tr>
<tr>
<td>2.1</td>
<td>Structure of the literature review</td>
<td>8</td>
</tr>
<tr>
<td>2.2</td>
<td>Classification of knowledge</td>
<td>10</td>
</tr>
<tr>
<td>2.3</td>
<td>Cynefin decision making framework</td>
<td>12</td>
</tr>
<tr>
<td>2.4</td>
<td>Organizational knowledge management processes</td>
<td>13</td>
</tr>
<tr>
<td>2.5</td>
<td>Single-loop learning</td>
<td>14</td>
</tr>
<tr>
<td>2.6</td>
<td>Double-loop learning</td>
<td>15</td>
</tr>
<tr>
<td>2.7</td>
<td>The SECI model</td>
<td>16</td>
</tr>
<tr>
<td>2.8</td>
<td>A data cube in Microsoft SQL Server 2005 Analysis Services</td>
<td>18</td>
</tr>
<tr>
<td>2.9</td>
<td>Mapping of KM and OL</td>
<td>26</td>
</tr>
<tr>
<td>2.10</td>
<td>An example of learning curve</td>
<td>28</td>
</tr>
<tr>
<td>2.11</td>
<td>A schematic diagram of a typical knowledge based system</td>
<td>36</td>
</tr>
<tr>
<td>2.12</td>
<td>Landscape of narratives</td>
<td>39</td>
</tr>
<tr>
<td>2.13</td>
<td>A system dynamics diagram for pesticide application</td>
<td>41</td>
</tr>
<tr>
<td>2.14</td>
<td>A system dynamics diagram for wolf sheep predation</td>
<td>42</td>
</tr>
<tr>
<td>2.15</td>
<td>Details for agents, activities, and decision task in OrgAHead</td>
<td>45</td>
</tr>
<tr>
<td>2.16</td>
<td>A screenshot of a web based beer game</td>
<td>46</td>
</tr>
<tr>
<td>2.17</td>
<td>A screenshot of narrative simulation on farm safety</td>
<td>48</td>
</tr>
<tr>
<td>2.18</td>
<td>A story developed by UNIVERSE</td>
<td>52</td>
</tr>
<tr>
<td>2.19</td>
<td>A story developed by BURTUS</td>
<td>54</td>
</tr>
<tr>
<td>2.20</td>
<td>A story developed by MINSTREL</td>
<td>55</td>
</tr>
<tr>
<td>2.21</td>
<td>A story developed by MEXICA</td>
<td>55</td>
</tr>
<tr>
<td>2.22</td>
<td>A screenshot of ProtoPropp</td>
<td>56</td>
</tr>
<tr>
<td>2.23</td>
<td>The architecture of typical ANN</td>
<td>62</td>
</tr>
<tr>
<td>2.24</td>
<td>A schematic diagram of genetic algorithm</td>
<td>65</td>
</tr>
<tr>
<td>2.25</td>
<td>An example of concept map</td>
<td>71</td>
</tr>
<tr>
<td>2.26</td>
<td>A concept map created by a concept map tool</td>
<td>72</td>
</tr>
<tr>
<td>2.27</td>
<td>A screenshot of TextAnalyst</td>
<td>75</td>
</tr>
<tr>
<td>3.1</td>
<td>Research methodology</td>
<td>81</td>
</tr>
<tr>
<td>3.2</td>
<td>A comparison between traditional approach and computational narrative simulation approach</td>
<td>82</td>
</tr>
<tr>
<td>Figure</td>
<td>Description</td>
<td></td>
</tr>
<tr>
<td>--------</td>
<td>-------------</td>
<td></td>
</tr>
<tr>
<td>3.3</td>
<td>Traditional narrative structure and multi-linear narrative structure</td>
<td></td>
</tr>
<tr>
<td>3.4</td>
<td>A framework of computational narrative simulation system (CNSS)</td>
<td></td>
</tr>
<tr>
<td>3.5</td>
<td>A schematic diagram of the KBS in the CNSS</td>
<td></td>
</tr>
<tr>
<td>3.6</td>
<td>The structural and unstructured parts of a case</td>
<td></td>
</tr>
<tr>
<td>3.7</td>
<td>Conversion of an unstructured narrative into a structural concept map</td>
<td></td>
</tr>
<tr>
<td>3.8</td>
<td>A schematic diagram of the NSCS in the CNSS</td>
<td></td>
</tr>
<tr>
<td>3.9</td>
<td>A schematic diagram of construction of a multi-linear narrative</td>
<td></td>
</tr>
<tr>
<td>3.10</td>
<td>Narrative construction toolkit</td>
<td></td>
</tr>
<tr>
<td>3.11</td>
<td>A schematic diagram of the FACM</td>
<td></td>
</tr>
<tr>
<td>3.12</td>
<td>An example of conjunction problem</td>
<td></td>
</tr>
<tr>
<td>3.13</td>
<td>An example of case encoding</td>
<td></td>
</tr>
<tr>
<td>3.14</td>
<td>The membership function of the normalized frequency</td>
<td></td>
</tr>
<tr>
<td>3.15</td>
<td>The membership function of the relationship between concepts</td>
<td></td>
</tr>
<tr>
<td>3.16</td>
<td>The clipped membership function of the relationship between concepts</td>
<td></td>
</tr>
<tr>
<td>3.17</td>
<td>A schematic diagram of the adaptive time-series modeling method</td>
<td></td>
</tr>
<tr>
<td>3.18</td>
<td>An illustrative example of narrative construction</td>
<td></td>
</tr>
<tr>
<td>3.19</td>
<td>The schematic diagram of the hybrid case-based reasoning</td>
<td></td>
</tr>
<tr>
<td>3.20</td>
<td>The similarity of fuzzy sets</td>
<td></td>
</tr>
<tr>
<td>3.21</td>
<td>Fuzzy set of motivation and joining activity intensity</td>
<td></td>
</tr>
<tr>
<td>3.22</td>
<td>An example of the SACM</td>
<td></td>
</tr>
<tr>
<td>3.23</td>
<td>Knowledge elicitation of the SACM</td>
<td></td>
</tr>
<tr>
<td>3.24</td>
<td>Knowledge inference of the SACM</td>
<td></td>
</tr>
<tr>
<td>3.25</td>
<td>The membership functions of diameter</td>
<td></td>
</tr>
<tr>
<td>3.26</td>
<td>The membership functions of unit price</td>
<td></td>
</tr>
<tr>
<td>3.27</td>
<td>The SACM that assimilates 1 record</td>
<td></td>
</tr>
<tr>
<td>3.28</td>
<td>The SACM that assimilates 2 records</td>
<td></td>
</tr>
<tr>
<td>3.29</td>
<td>An aggregated fuzzy set of this example</td>
<td></td>
</tr>
<tr>
<td>4.1</td>
<td>Experimental flow of the FACM evaluation</td>
<td></td>
</tr>
<tr>
<td>4.2</td>
<td>Screenshot of the application of the FACM</td>
<td></td>
</tr>
<tr>
<td>4.3</td>
<td>Recall and precision of the baseline and the FACM (Abstracts)</td>
<td></td>
</tr>
<tr>
<td>4.4</td>
<td>Recall and precision of the baseline and the FACM (News)</td>
<td></td>
</tr>
<tr>
<td>4.5</td>
<td>Recall and precision of the FACM against word count (Abstracts)</td>
<td></td>
</tr>
<tr>
<td>4.6</td>
<td>Recall and precision of the FACM against word count (News)</td>
<td></td>
</tr>
</tbody>
</table>
List of Figures

Figure 4.7: An example of the resulted automatic concept map ......................... 149
Figure 4.8: Experimental flow of the narrative prediction evaluation .................. 149
Figure 4.9: Recall rate of the FACM ................................................................. 150
Figure 4.10: Precision rate of the FACM ........................................................... 150
Figure 4.11: Results of recall and precision for time interval is 1 month .............. 153
Figure 4.12: Results of recall and precision for time interval is 2 months ............ 153
Figure 4.13: Results of recall and precision for time interval is 3 months .......... 154
Figure 4.14: Results of recall and precision for time interval is 4 months .......... 154
Figure 4.15: Results of recall and precision for time interval is 5 months .......... 155
Figure 4.16: Results of recall and precision for time interval is 6 months .......... 155
Figure 4.17: Experimental flow of the HCBR evaluation ................................. 156
Figure 4.18: Results of HCBR, CBR and RBR in after intake (intervention) ....... 157
Figure 4.19: Results of HCBR, CBR and RBR in during assessment (intervention) 158
Figure 4.20: Results of HCBR, CBR and RBR in after review (intervention) ....... 158
Figure 4.21: Results of HCBR, CBR and RBR in after intake (intensity) ............ 159
Figure 4.22: Results of HCBR, CBR and RBR in during assessment (intensity) ... 159
Figure 4.23: Results of HCBR, CBR and RBR in after review (intensity) .......... 160
Figure 4.24: Experimental flow of the first SACM evaluation ......................... 161
Figure 4.25: The results of SACM, CBR and human ...................................... 164
Figure 4.26: Experimental flow of the second SACM evaluation ...................... 164
Figure 4.27: The results of the SACM and the CBR ........................................ 166
Figure 5.1: The workflow of adolescent early intervention .............................. 170
Figure 5.2: A snapshot of the workflow for managing a case .......................... 172
Figure 5.3: Results of users’ feedbacks on the proposed knowledge-based system 173
Figure 5.4: A snapshot of the CNSS ............................................................... 174
Figure 5.5: Experimental group and control group of narrative simulation evaluation .......................................................... 178
List of Tables

LIST OF TABLES

Table 2.1: Various definitions of knowledge management ........................................ 21
Table 2.2: Various definitions of organizational learning ........................................ 24
Table 2.3: Summary of facilitating factors for organizational learning ..................... 27
Table 2.4: Limitations of conventional approaches for organizational learning ......... 49
Table 2.5: Example of an error-correcting rule .................................................... 69
Table 3.1: Differences between traditional narrative simulation and the CNS .......... 84
Table 3.2: Examples of the variation types .......................................................... 103
Table 3.3: A simplified case base ................................................................. 122
Table 3.4: Results of the CBR ................................................................. 123
Table 3.5: A simplified knowledge repository .................................................... 132
Table 3.6: Temporary results of the SACM that assimilates 1 record .................... 133
Table 3.7: Results of the SACM that assimilates 1 record .................................. 134
Table 3.8: Temporary results of the SACM that assimilates the second record ....... 135
Table 3.9: Temporary results of the SACM that assimilates 2 records ................. 136
Table 3.10: Results of the SACM that assimilates 2 records ............................... 137
Table 3.11: The SACM of the example of enquiry ............................................ 137
Table 3.12: Activation level of each concept of this example ............................... 138
Table 4.1: Output propositions of the sample text ............................................ 144
Table 4.2: Evaluation results of the FACM ..................................................... 146
Table 4.3: Output propositions of the example text ............................................ 148
Table 4.4: Results of the FACM ................................................................. 150
Table 4.5: Experimental results of accuracy of proposition prediction ............... 152
Table 4.6: The structure of a quotation in the knowledge repository .................... 152
Table 4.7: Experiment results of SACM, CBR and human layman ..................... 163
Table 5.1: User evaluation results of the CNSS .............................................. 177
Table 5.2: Results of learning outcome of the users ........................................ 179
LIST OF ABBREVIATIONS

1. A Nearly-New Information Extraction System (ANNIE)
2. Artificial Intelligence (AI)
3. Artificial Neural Networks (ANN)
4. Attribute Concept Map (ACM)
5. Autoregressive (AR)
6. Baptist Oi Kwan Social Service (BOKSS)
7. Case-based Reasoning (CBR)
8. Centre of Gravity (COG)
9. Computational Intelligence (CI)
10. Computational Narrative Simulation (CNS)
11. Computational Narrative Simulation System (CNSS)
12. Concept-Relation-Concept (CRC)
13. Constrained Fuzzy Spreading Activation (CFSA)
14. Constrained Spreading Activation (CSA)
15. Decision tree (DT)
16. Enhanced Least Mean Square (ELMS)
17. Fuzzy-Associated Concept Mapping (FACM)
18. General Architecture for Text Engineering (GATE)
19. Genetic Algorithm (GA)
20. Hybrid Case-based Reasoning (HCBR)
21. Information Technology (IT)
22. Inverse Document Frequency (IDF)
23. Knowledge Management (KM)
24. Knowledge Repository (KR)
25. Knowledge-based System (KBS)
26. Multi-agent Simulation (MAS)
27. Multilayer Perception (MLP)
28. Mutual Information (MI)
29. Narrative Simulation Construction System (NSCS)
30. Natural Language Generation (NLG)
31. Natural Language Processing (NLP)
List of Abbreviations

32. Online Analytical Processing (OLAP)
33. Organizational Learning (OL)
34. Part of Speech (POS)
35. Rule-based Reasoning (RBR)
36. Scientific Web intelligence (SWI)
37. Self-Associated Concept Mapping (SACM)
38. Spreading Activation (SA)
39. Sum of Squared Errors (SSE)
CHAPTER 1 INTRODUCTION

1.1 Research background

With the progressive development of support systems in business and industry, workers at all levels are required to respond to increasingly challenging customer and market demands. Human work is becoming more and more complex. There is a shift from less complicated routine work towards greater complexity of work (Wiig, 1993). Enterprises these days depend more and more on detailed knowledge of people and processes in order to sustain their competitive advantage. Knowledge assets are attracting more and more attention from all fields including the academic research field and from industry.

Managers and scholars are increasingly aware of the need for rapid learning throughout the organization. Prokesch (1997) said that “Learning is at the heart of a company’s ability to adapt to a rapidly changing environment” and “Any organizations that think they do everything the best and need not learn from others are incredibly arrogant and foolish”. Learning has been considered from a strategic perspective as a source of heterogeneity among organizations as well as a basis for a possible competitive advantage (Grant, 1996, Lei et al, 1996 and 1999).

There is a growing consensus that organizations must become more effective learners. In particular, these environmental forces are driving many manufacturers toward greater agility, with attendant increases in product and service diversity and accelerating product and service innovation (Pine, 1993). Individual worker must constantly adapt to the changing tasks. For example, production lines that used to run...
for years are now reconfigured every few months in industries such as electronics assembly and apparel manufacturing. When this broad trend is combined with accelerating process innovation, greater cross-training and more aggressive restructuring of work are carried out. It seems inevitable that future workers will have to master new tasks far more often (Mustafa and David, 1998). As depicted in Figure 1.1, this trend promises to truncate the learning curves of individual workers. It means that workers spend more of their working lives on learning in order to sustain productivity. Hence, there is a need for people and organizations to learn quickly to adapt to the changes (Prusak, 1997).

Figure 1.1: Shifting of learning curves for individual workers (Adapted from Mustafa and David, 1998)

Organizational learning (OL) is a field for describing how organizations can learn (García and Vañó, 2002). Probst and Büchel (1997) define OL as “the ability of the institution as a whole to discover errors and correct them, and to change the organization’s knowledge base and values so as to generate new problem-solving skills and new capacity for action.” To achieve OL, a number of facilitating factors have been considered. In particular, the major component of the factors involved in
the learning mechanism is action (Argyris, 1977; Weick and Westley, 1996; Tannenbaum, 1997). Current theories of learning also reveal that the knowledge creation process cannot be separated from the process of applying it (Brown and Duguid, 1991). The effective integration of working and learning is a fundamental requirement for businesses to remain competitive. Since people learn through actions, it is important for people to be exposed to the problems so that they can gain more experience. However, the outcomes of incorrect actions can be painful and costly (Carley, 2002a). Simulation provides an important means for people to try their actions out in a way that is safe, cost effective, fast, appropriate, flexible, and ethical (Carley, 2002a). It has been widely used in skill development in diverse fields such as flight instruction and industrial training.

Recently, more and more researchers have noted the importance of narrative knowledge. Narrative knowledge usually takes the form of organization stories which are collected within the organization. Some of the researchers have introduced narrative into simulation with the aim of providing training to solve organizational problems (e.g. McCrary and Mazur, 1999). Such kind of simulation is called narrative simulation. Unlike traditional simulation work, narrative simulation requires a refinement of the principles of the design of the simulation exercise, as well as evidence of specific problem characteristics. It has been proven that narrative simulation is very useful in facilitating in-depth learning and reflective learning (Cole, 1997).

However, traditional methods of data acquisition and construction of narrative simulation are labour intensive and time consuming. Most of the 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 and hence the collected narratives easily become outdated. It is inadequate for coping with this fast moving world in which knowledge within organizations is changing rapidly. Furthermore, most of the existing narrative simulation methods make use of a single previous narrative directly. The coverage of knowledge is limited and the quality of narrative simulation relies heavily on the experience of the simulation designer.

1.2 Problem identification

In the light of the research background described in Section 1.1, the present study aims to develop and apply a novel systematic methodology of making use of organizational narrative knowledge and narrative simulation efficiently and effectively for achieving organizational learning. The following key issues have been identified that should be addressed:

(i) How to continuously update and make use of existing narrative knowledge efficiently and effectively so as to facilitate the data collection process.

(ii) How to create a platform for people to test their actions and consequences in a cost effective, fast, appropriate, flexible, and ethical way

(iii) How to efficiently and effectively convert the unstructured narrative text into a structural format that can be easily processed by computers

(iv) How to combine a number of narratives into a single narrative simulation so as to provide a wider coverage of the learning area

(v) How to achieve proactive learning and provide scenarios that would possibly happen in the near future
(vi) How to facilitate the construction process of narrative simulation so that narrative simulation can be constructed more efficiently and effectively

(vii) How to evaluate the proposed methodology

(viii) When is the proposed method useful or not useful under what conditions, limitations or assumptions?

(ix) What kinds of system modifications can be suggested to overcome the limitations?

1.3 Project objectives

Based on the problem statement, the specific objectives of this research are given as follows.

(i) To study the existing methods and technologies of organizational learning (OL).

(ii) To develop a computational narrative simulation (CNS) method for managing narrative knowledge and automatically constructing narrative simulation for achieving OL.

(iii) To develop a computational narrative simulation system (CNSS) for realizing the CNS method.

(iv) To develop computational intelligent algorithms for the implementation of the CNSS and validate the performance of the algorithms by a series of experiments.

(v) To develop a prototype of the CNSS and evaluate the performance of the CNSS through a series of experiments and trial implementation at a selected reference site.
Chapter 1 Introduction

1.4 Organization of the thesis

This thesis is composed of seven chapters. Chapter 1 provides the background and motivation of this research. The nature of organizational knowledge, the knowledge processes, and the state-of-art of organizational learning are discussed in Chapter 2. A literature review of the facilitating factors of organizational learning, existing organizational learning methods and practices adopted by industries, the limitations of traditional theories, and the technologies and techniques for organizational learning are also discussed.

In Chapter 3, the research methodology for the computational narrative simulation (CNS) is presented. Hence, a computational narrative simulation system (CNSS) is established and built. The CNSS consists of a knowledge-based system (KBS) and a narrative simulation construction system (NSCS) for achieving the knowledge processes. The KBS, the NSCS, the knowledge repository, and the four computational intelligent algorithms (the fuzzy association concept mapping, the narrative prediction and construction, hybrid case-based reasoning, and the self-associated concept mapping) that support the CNSS are described in detail in this chapter.

Chapter 4 and Chapter 5 focus on the experimental evaluation of the intelligent algorithms and the case study of the proposed methodology, respectively. In Chapter 4, a series of experiments have been carried out for measuring the performance of the computational intelligent algorithms for the CNSS. The capability and applicability of the system in a real-life environment have been studied in Chapter 5 through a practical implementation of a prototype CNSS in a selected reference site.
Chapter 1 Introduction

The results of the system evaluation are also discussed. Chapter 6 is an overall conclusion of the thesis, and some suggested areas for further work are explored in Chapter 7.
This chapter provides a review of literature relevant to the study. The structure of the literature review is shown in Figure 2.1. The nature of organizational knowledge is discussed in the beginning of this chapter. A review on how organizations create, store, transfer and share, and apply organizational knowledge is discussed in the section devoted to knowledge processes. Then, an overview of knowledge management (KM) and organization learning (OL) is provided. After that, the facilitating factors for achieving OL are discussed. Then a literature review is conducted on the existing OL approaches.

In particular, on-the-job training, e-learning, and narrative simulation are
mainly applied for the knowledge creation process (Alavi and Tiwana, 2003). Narrative databases are used for knowledge storage, retrieval, and sharing (Snowden, 2002b). Computational simulation goes with knowledge applications (Carley, 2002b). Action research and organizational storytelling belong to knowledge sharing and transfer (Gargiulo, 2005 and 2006). The author adopts Liao’s (2005) thinking that considers expert systems and decision support systems are under broad sense of knowledge-based systems (KBS), and KBS covers knowledge storage, transfer and sharing, and application. The limitations of these approaches are also discussed so as to highlight the research opportunity. The last section of this chapter reviews different kinds of technologies that support this research.

2.1 Organizational knowledge

Organizational knowledge is the knowledge created, traded and used in organizations. It can be categorized according to whether it is tacit or explicit, or by its degree of diffusion and codification, degree of generalization, and degree of complexity. Tacit knowledge refers to knowledge which is only known by an individual and so is difficult to communicate to other people in an organization (Nonaka and Takeuchi, 1995). It is deeply rooted in an individual's actions and experience as well as in ideals and values (Nonaka and Konno, 1998). It cannot be codified, and can only be transmitted via training or gained through personal experience (e.g. subjective insights, intuitions, and hunches). It may seem to be a simple idea but its implications are large and far reaching. If important knowledge is tacit, training newcomers in an organization becomes more time consuming, because they must be given time to learn on their own while doing, which reduces overall efficiency. Explicit knowledge can be expressed in words and numbers and shared in
the form of data, scientific formulae, specifications, manuals, etc. It can be readily transmitted between individuals formally and systematically (Nonaka and Konno, 1998).

Max Boisot (1983) distinguishes two dimensions and each is dichotomized to yield a fourfold classification of knowledge. As shown in Figure 2.2, one dimension gives an account of the codification of a domain of knowledge, and the other gives an account of the diffusion of that knowledge across a population. Four different kinds of knowledge are described:

![Figure 2.2: Classification of knowledge (adapted from Max Boisot, 1983)](image)

(i) Public knowledge is codified and diffused, such as textbooks and newspapers.

(ii) Proprietary knowledge is codified but not diffused, such as patents and official secrets.

(iii) Personal knowledge is neither codified nor diffused, such as biographical
(iv) Common sense is not codified but widely diffused.

Cynefin is a decision making framework produced by Snowden (2000a) which has been used in KM. As shown in Figure 2.3, it has five domains which are characterized by the relationship between cause and effect.

(i) Simple domain: the relationship between cause and effect is obvious to all. The approach to learning is through: Sense – Categories – Response.

(ii) Complicated domain: the relationship between cause and effect requires analysis or some other forms of investigation and/or the application of expert knowledge. The approach to learning is through: Sense – Analysis – Response.

(iii) Complex domain: the relationship between cause and effect can only be perceived in retrospect, but not in advance. The approach to learning is to Probe – Sense – Respond.

(iv) Chaotic domain: there is no relationship between cause and effect at a systems level. The approach to learning is to Act – Sense – Respond.

(v) Disorder domain: the state of not knowing what type of causality exists.

Organizational knowledge can also be classified into scientific knowledge and narrative knowledge. Scientific knowledge is generalization of data which does not vary from individual to individual. It must be clear and always takes the form of rules like “whenever A, then B” or in terms of mathematics. It must be correctable so that it can be re-examined and modified as necessary to maintain its validity. In contrast to the scientific knowledge that guides the engineer or the chemist,
managers are often informed by different types of knowledge. This is sometimes referred to “narrative knowledge” or “experiential knowledge”. This kind of knowledge comes from experience and resides in stories and narratives of how people in the real-world deal with real life problems, successfully or unsuccessfully. It is how people make sense of their lives, and it plays an important role in each individual's identification of themselves (Kerby, 1991).

![Cynefin decision making framework](adapted from Snowden, 2000a)

Narrative knowledge usually takes the form of organizational stories which are collected within the organization (Czarniawska, 1998). Narrative knowledge facilitates understanding and stimulates imagination. People can have a more comprehensible understanding on their difficulties and challenges by listening to the other’s similar stories. These stories help people to adapt to the experience and discover new innovative ideas from others in order to solve their own problems (Lämsä and Sintonen, 2006). Since narrative knowledge is highly related to OL, it is the major focus in the present study.
2.2 Knowledge processes in organizations

There are different knowledge processes in KM and OL. In the present study, the author adopts the knowledge management framework developed by Alavi and Leidner (2001). According to this framework, organizations consist of four knowledge processes: creation; storage and retrieval; transfer and sharing; and application. As shown in Figure 2.4, new organizational know-how is created in the knowledge creation process. The created knowledge is needed to be stored and retrieved in organizations. It is then transferred to or shared with members within organizations. The knowledge is then used in decision-making and problem solving in the knowledge application process. During the transfer, sharing and application processes, new knowledge may be created by individuals and groups in organizations.

![Figure 2.4: Organizational knowledge management processes](image)

2.2.1 Knowledge creation

Knowledge creation refers to the development of new organizational know-how and capability (Nonaka and Nishiguchi, 2001). March and Olsen (1975) believe that
individual beliefs lead to individual action, which in turn may lead to an organizational action and response from the environment. It may induce improved individual beliefs and the cycle then repeats. Knowledge creation and learning occurs as better beliefs produce better actions.

Argyris and Schon (1978) and Argyris (1994) describe three types of OL: single-loop, double-loop learning and deutero-learning. As shown in Figure 2.5, individuals, groups or organizations modify their actions according to the difference between expected and obtained outcomes and the entities carry on with their present believes, policies and goals in single-loop learning. It has also been referred to as lower-level learning by Fiol and Lyles (1985), adaptive learning or coping by Senge (1990), and non-strategic learning by Dodgson (1993).

![Figure 2.5: Single-loop learning (adapted from Argyris, 1990)](image)

In double-loop learning as shown in Figure 2.6, the entities question the values, assumptions, policies and objectives that lead to the actions in the first place. If they are able to view and modify them, then second-order or double-loop learning has been taken place. It is called higher-level learning by Fiol and Lyles (1985), generative learning by Senge (1990), and strategic learning by Dodgson (1993). Deutero-learning focuses on learning how to achieve single-loop and double-loop learning. Learning must be aware, otherwise learning will not occur. The awareness
makes the organization recognize that an appropriate environment and appropriate processes need to be created for facilitating learning.

![Diagram of Double-loop learning](adapted_from_Argyris_1990)  
**Figure 2.6: Double-loop learning (adapted from Argyris, 1990)**

Crossan et al.’s (1999) proposed 4I framework of OL, which argue that learning takes place on the individual, group, and organizational levels, and 4 sub-processes link the 3 levels, involving both behavioural and cognitive changes. Mintzberg et al. (1998) summarize the 4 sub-processes. Intuiting is a subconscious process that occurs at the level of the individual. It is the start of learning and must happen in a single mind. Interpreting then picks up on the conscious elements of this individual learning and shares it at the group level. Integrating follows to change collective understanding at the group level and to build bridges to the level of the whole organization. Finally, institutionalizing incorporates that learning across the organization by imbedding it in its systems, structures, routines, and practices.

On the other hand, Nonaka and Takeuchi (1995) developed SECI model as shown in Figure 2.7, which is a four stage spiral model of OL. They started by differentiating the concept of “tacit knowledge” from “explicit knowledge” and describe a process of alternating between the two. The tacit knowledge of key
personnel within the organization can be made explicit, codified in manuals, and incorporated into new products and processes. This process is called “externalization”. The reverse process from explicit to implicit is called “internalization”. It involves employees internalizing an organization's formal rules, procedures, and other forms of explicit knowledge. They also use the term “socialization” to denote the sharing of tacit knowledge, and the term “combination” to denote the dissemination of codified knowledge. According to this model, knowledge creation and OL take a path of socialization, externalization, combination, internalization, socialization, externalization, combination, etc. in an infinite spiral.

![Figure 2.7: The SECI model (adapted from Nonaka and Takeuchi, 1995)](image)

Recently, Snowden (2002a) argues that the focus on tacit-explicit conversions is no longer adequate for today’s OL. He believes that “people always know more than they can say, and always say more than they can write down”. This leads to a new focus on the management of narrative for OL. Through the patterns of narrative flow, stories allow people to understand the nature of those interactions, and stories allow
people to intervene in order to pattern the narrative and thereby the culture and attitudes of those interactions within an organization. Thus, narrative techniques are the key to enable more effective decision-making, and to disrupt or change the perspective to reveal new insights and understanding.

On the whole, OL is a social process involving interactions among many individuals for creating, capturing, transferring, and applying knowledge. OL can be distinguished into two different processes that are adaptive learning and proactive learning. Adaptive learning is changes that have been made in reaction to the changing environmental conditions. Proactive learning is changes that have been made goes beyond the simple reacting to environmental changes. OL can be achieved by the transformation of knowledge (tacit-explicit conversions) and the management of narrative.

2.2.2 Knowledge storage and retrieval

Knowledge storage and retrieval refers to development of organization’s memory and the means for accessing its content (Alavi and Tiwana, 2003). Organizational memory can be divided into 2 types: internal and external. Internal memory refers to knowledge stored in the minds of organizational participants. It consists of individuals’ skills and the organizational culture (Walsh and Ungson, 1991). External memory refers to codified and explicit organizational knowledge, which include formal policies and procedures, and manuals and computer files.

The key technologies for the storage and retrieval of codified organizational knowledge are data warehousing, Online analytical processing (OLAP) and
knowledge repositories, etc. Traditionally, organizations capture transactional data (e.g. retail sales, supplier orders, etc.) in separate databases. A data warehouse is a centralized repository to integrate and summarize such data, which helps convert large volumes of raw data into smaller chunks of interlinked information (Kimball, 1996; Inmon, 1996). It is manipulated through OLAP tools, which offer visualization and navigation mechanisms of multidimensional data views commonly called data cubes. A data cube is a multidimensional representation used to view data in a warehouse (Chaudhuri & Dayal, 1997). A screenshot of the multidimensional representation is shown in Figure 2.8.

Figure 2.8: A data cube in Microsoft SQL Server 2005 Analysis Services (SQL Server Training, 2008)

Similar to data warehouses, knowledge repositories bring together content from various data sources, providing a unified access point and reducing the cost for
knowledge search (Hansen, 1999). Unlike data warehouses, knowledge repositories store not only highly structured data such as transactional data, but also store relatively unstructured content such as conversational discussion threads.

2.2.3 Knowledge transfer and sharing

In order for knowledge to have wide organizational impact, it needs to be either transferred or shared. Knowledge transfer and sharing can be conceptualized as two ends of a continuum. Transfer involves the focused and purposeful communication of knowledge from a sender to a known receiver (King, 2006a). Knowledge sharing is less-focused dissemination, such as through a repository, to people who are usually unknown to the contributor (King, 2006b). Many of the points on the continuum involve some combinations of the two processes and both processes may involve individuals, groups or organizations as either senders or receivers, or both.

There are two models for knowledge transfer and sharing: the network model and the knowledge stock model (Alavi and Tiwana, 2003). The network model focuses on facilitating people-to-people transfer of knowledge via electronic communication channels such as emails, online chat rooms, and video conferencing. The stock model focuses on the electronic transfer of codified knowledge to and from computerized knowledge repositories, such as enterprise information portal. An enterprise information portal enables the knowledge transfer from repositories to and from individuals through a central access point and a web browser interface.

2.2.4 Knowledge application

Once knowledge is transferred and shared, it can be used or applied through a
process of elaboration (the development of different interpretations), infusion (the identification of underlying issues), and thoroughness (the development of multiple understandings by different individuals or groups) (King and Ko, 2001) in order to facilitate innovation, collective learning, individual learning, and collaborative problem solving (King, 2005). It can also be embedded in the practices, systems, products and relationships of the organization through the creation of knowledge-intensive organizational capabilities (Levitt and March, 1988).

2.3 Organizational learning and knowledge management

2.3.1 Overview of knowledge management

Knowledge management (KM) has emerged as a very successful organization practice and has been extensively treated in a large body of academic work. KM deals with knowledge processes and uses an interdisciplinary approach to address issues and challenges in the identification, capture, analysis, storage, retrieval, transfer, exploitation, creation and security of knowledge within an enterprise. It is the key to competitive advantage in the knowledge economy, leading to better customer care, increased return-on-investment, faster time-to-market, enhanced performance, and innovation (Davenport, et. al, 2006). KM has been utilized successfully by major corporations, government agencies, and international organizations, such as BP/AMOCO, GE, Ford Motor Company, KPMG, Gartner, the World Bank, and the U.S. State Department. The term ‘knowledge management’ was coined by Karl Wiig in a 1986 Swiss conference sponsored by the United Nations (Beckman, 1999). Table 2.1 provides some representative definitions of KM.
Table 2.1: Various definitions of knowledge management

<table>
<thead>
<tr>
<th>Definitions</th>
<th>Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>KM is defined as focusing on determining, organizing, directing, facilitating, and monitoring knowledge related practices and activities required to achieve the desired business strategies and objectives.</td>
<td>Wiig, 1993</td>
</tr>
<tr>
<td>KM addresses the generation, representation, storage, transfer, transformation, application, embedding and protecting of organizational knowledge.</td>
<td>Hedlund, 1994</td>
</tr>
<tr>
<td>KM is about generating, representing, accessing, transferring, embedding and facilitating knowledge and knowledge process developing a culture that values knowledge that shares, values and uses knowledge.</td>
<td>Marshall et. al., 1996</td>
</tr>
<tr>
<td>KM is knowledge creation, which is followed by knowledge interpretation, knowledge dissemination and use, and knowledge retention and refinement.</td>
<td>De Jarnet, 1996</td>
</tr>
<tr>
<td>KM applies systematic approaches to find, understand and use knowledge to create value.</td>
<td>O’Dell, 1997</td>
</tr>
<tr>
<td>KM is the process of creating, capturing and using knowledge to enhance organizational performance.</td>
<td>Bassi, 1997</td>
</tr>
<tr>
<td>KM can be defined as the identification, optimization and active management of intellectual assets, either in the form of explicit knowledge held in artifacts or as tacit knowledge possessed by individuals or communities.</td>
<td>Snowden, 1998</td>
</tr>
<tr>
<td>KM caters to the critical issues of organizational adaptation, survival and competence in face of increasingly discontinuous environmental change. Essentially it embodies organizational processes that seek synergistic combination of data and information processing capacity of information technologies, and the creative and innovative capacity of human beings.</td>
<td>Malhotra, 1998</td>
</tr>
<tr>
<td>KM is about harnessing the social and intellectual capital of individuals in order to improve organizational learning capability.</td>
<td>Swan et. al., 1999</td>
</tr>
<tr>
<td>KM is the formalization of and access to experience, knowledge, and expertise that create new capabilities, enable superior performance, encourage innovation, and enhance customer value.</td>
<td>Beckman, 1999</td>
</tr>
<tr>
<td>KM is the process of systematically and actively managing and leveraging the stores of knowledge in an organization.</td>
<td>Laudon and Laudon, 1999</td>
</tr>
<tr>
<td>KM is achieving organizational goals through the strategy-driven motivation and facilitation of knowledge workers to develop, enhance and use their capability to interpret data and information (by using available sources of information, experience, skills, culture, character, personality, feelings, etc.) through a process of giving meaning to these data and information.</td>
<td>Beijerise, 1999</td>
</tr>
<tr>
<td>Knowledge management is about the support of knowledge sharing.</td>
<td>Huysman and De Wit, 2000</td>
</tr>
<tr>
<td>Distinct but interdependent processes of knowledge creation, knowledge storage and retrieval, knowledge transfer and knowledge application.</td>
<td>Alavi and Leidner, 2001</td>
</tr>
</tbody>
</table>
Some definitions are not predicated on information technology (IT) such as Marshall et al. (1996) and De Jarnet (1996). This emphasizes the importance of non-technical or soft issues. In contrast, some definitions are predicated to IT such as Malhotra (1998), Snowden (1998) and Bassi (1997). This emphasizes the integral importance of technology for KM. The wide range of definitions also reflect the fact that people working in the field of KM come from a wide range of disciplines such as psychology, management science, organizational science, sociology, strategy, production engineering and so on. In this thesis, the focus is upon an organization’s capacity to learn and produce knowledge, as well as an emphasis on its capture and distribution.

2.3.2 Organizational learning (OL) and its relationships to KM

OL is an area of describing how an organization learns. Scholars believe that an organization is able to sense changes in signals from its internal and external environment and adapt accordingly. OL is an area of knowledge within organizational theory that studies models and theories about the way an organization learns. The concept of OL has expanded greatly over the past few years. OL is regarded as a powerful tool to improve the understanding of organizations as well as the performance of organizations. Stata (1996) argues that the rate at which individuals and organizations learning may become the only sustainable competitive advantage, especially in knowledge-intensive industries. Thus, many researchers and practitioners are interested in the study of OL and they are delegated to deal with the subject of OL. The literature on OL has been attempting to study several major areas, which include the definition of OL, the process of OL to take place, the content of learning, and the factors facilitating or inhibiting OL. The following provides a brief
summary of these areas.

There are numerous definitions of OL found in the literature. Some of them are provided in Table 2.2. According to Argyris (1977), OL is a process of detecting and correcting error. By the definition of Fiol and Lyles (1985), OL means the process of improving actions through better knowledge and understanding. Dodgson (1993) describes OL as the way firms build, supplement, and organize knowledge and routines around their activities and within their culture and adapt and develop organizational efficiency by improving the use of the broad skills of their workforces. Probst and Büchel (1997) have similar view to Argyris, they defined OL as “the ability of the institution as a whole to discover errors and correct them and to change the organization’s knowledge base and values so as to generate new problem solving skills and new capacity for action”.

DiBella and Nevis (1998) define OL as the capacity or process within an organization to maintain or improve performance based on experience. They look at the OL as a social process whereby some insight or knowledge, created either by an individual worker alone or by team, becomes accessible to others. Huysman (2000) gives the definition where the focus is on collective knowledge construction: “OL is the process through which an organization constructs knowledge or reconstructs existing knowledge”. García and Vañó (2002) not only start from the individual but also stress the collective pattern. They explained that OL can be understood as a collective phenomenon in which new knowledge is acquired by the members of an organization with the aim of developing the core competences in the firm, taking individual learning as the basic starting point.
## Table 2.2: Various definitions of organizational learning

<table>
<thead>
<tr>
<th>Definitions</th>
<th>Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>OL is a process of detecting and correcting error.</td>
<td>Argyris, 1977</td>
</tr>
<tr>
<td>OL is a process of improving actions through better knowledge and understanding.</td>
<td>Fiol and Lyles, 1985</td>
</tr>
<tr>
<td>OL is a process of people continually expanding their capacity to create the results they truly desire, a process of creating new and expansive patterns of thinking, and a process of people continually learning to see the whole together.</td>
<td>Senge, 1990</td>
</tr>
<tr>
<td>OL is not simply training individuals; it is a learning process at the whole organization level.</td>
<td>Pedler et. al., 1991</td>
</tr>
<tr>
<td>OL is a process of collaboratively conducted, collectively accountable change directed towards shared values or principles.</td>
<td>Watkins and Marsick, 1992</td>
</tr>
<tr>
<td>OL is the way firms build, supplement, and organize knowledge and routines around their activities and within their culture and adapt and develop organizational efficiency by improving the use of the broad skills of their workforces.</td>
<td>Dodgson, 1993</td>
</tr>
<tr>
<td>OL is the ability of the institution as a whole to discover errors and correct them and to change the organization’s knowledge base and values so as to generate new problem solving skills and new capacity for action.</td>
<td>Probst and Büchel, 1997</td>
</tr>
<tr>
<td>OL is the capacity or process within an organization to maintain or improve performance based on experience.</td>
<td>DiBella and Nevis, 1998</td>
</tr>
<tr>
<td>OL is the process through which an organization constructs knowledge or reconstructs existing knowledge.</td>
<td>Huysman, 2000</td>
</tr>
<tr>
<td>OL is a collective phenomenon in which new knowledge is acquired by the members of an organization with the aim of settling, as well as developing, the core competences in the firm, taking individual learning as the basic starting point.</td>
<td>García and Vañó, 2002</td>
</tr>
</tbody>
</table>

In the present study, the author agrees with the theorists (e.g. Argyris, 1977; Dodgson, 1993; García and Vañó, 2002) who emphasize the interrelationship between cognition and behavior and conclude that the learning process involves both cognitive and behavioral change. Individuals and groups learn by understanding and then acting, or by acting and then interpreting (Crossan, et al., 1995). For the definition of OL, this thesis adopts the thinking of Vera and Crossan (2003): OL is the process of change in individual and shared though and action, which is affected by and embedded in the institutions of the organization. When individual and group
learning becomes institutionalized, OL occurs and knowledge is embedded in repositories such as routines, systems, structures, and strategy.

Organizational learning (OL) and KM are closely interrelated, but they are rarely discussed together. Researchers in each field often fail to acknowledge the other and use different terminologies (Chiva and Alegre, 2005; Spender, 2008). Researchers in OL exclude the term “knowledge” from their studies and researchers in KM do the same with the term “learning”.

Start from Mark and Lyles (2003), they attempt to use a dichotomies of theory-practice and content-process to distinguish OL and KM. As shown in Figure 2.9, OL refers to the study of the learning process of and within organizations and largely from an academic point of view. OL often adopts a philosophical angle to understand the nature of knowledge that is contained within organizations. While KM generally adopts a technical approach which aims at creating ways of disseminating and leveraging knowledge in order to enhance organizational performance. They identify the organization’s knowledge assets, collect, store and optimize them in a managed manner and finally delivering the result to the locations where it can be integrated and turned into value (Teece, 2003). Therefore, KM has a more practical and performance agenda.

Due to the continuous development of OL and KM, the similarity between them increases and the difference decreases (Firestone and McElroy, 2004). The concerns of both fields are largely the same. By taking the process view and prescriptive view, OL is identical and approximate with KM respectively (Firestone and McElroy,
OL calls double-loop organizational learning processes, while KM calls knowledge processes. In the present study, the author agrees that OL is complementary to KM. KM needs OL and its expanding body of research work. OL needs the practitioner base of KM and its interest in problems and practice.

Figure 2.9: Mapping of KM and OL (adapted from Easterby-Smith and Lyles, 2003)

2.3.3 Facilitating factors for OL

In order to achieve OL, the importance of factors that facilitate OL has been outlined in the literature (Argyris 1977; Duncan and Weiss 1979; Hedberg, 1981; Senge, 1990; Ulrich et al., 1993; Nevis et al., 1995; Weick and Westley, 1996; Tannenbaum, 1997; Goh and Richards, 1997; Probst and Büchel, 1997). 13 factors are summarized and shown in Table 2.3.

Table 2.3 shows a consensus where there are several common factors that should be considered as important facilitating factors for OL. They include: promoting experimentation, implementing new idea and tolerating mistakes;
encouraging and supporting individual learning; shared vision among individuals and organization; supports of continuous training; and promoting team co-operation and support with open communications and discussion. Hence, these are the major objectives in the present study.

Table 2.3: Summary of facilitating factors for organizational learning

<table>
<thead>
<tr>
<th>Factors</th>
<th>Ref. No.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Promoting experimentation, implementing new idea and tolerating mistakes</td>
<td>1,3,5,6,7,8,9</td>
</tr>
<tr>
<td>Encouraging and supporting individual learning</td>
<td>1,2,3,4,8,9,10</td>
</tr>
<tr>
<td>Shared vision among individuals and organization</td>
<td>2,4,5,6,7</td>
</tr>
<tr>
<td>Support of continuous training</td>
<td>1,4,5,6,8</td>
</tr>
<tr>
<td>Promoting team co-operation and support with open communications and discussion</td>
<td>4,6,7,9</td>
</tr>
<tr>
<td>Leadership and empowerment committed to learning</td>
<td>3,5,6,9</td>
</tr>
<tr>
<td>Encouraging learning awareness in the organization</td>
<td>3,6</td>
</tr>
<tr>
<td>Heterogeneity and diversity</td>
<td>3,6</td>
</tr>
<tr>
<td>Transparency of the organization’s objectives and strategies</td>
<td>5,9</td>
</tr>
<tr>
<td>Encouraging learning awareness about the environment</td>
<td>6,9</td>
</tr>
<tr>
<td>Information systems for preventing information overloads</td>
<td>3</td>
</tr>
<tr>
<td>Systems thinking</td>
<td>4</td>
</tr>
<tr>
<td>Humor and improvisation</td>
<td>7</td>
</tr>
</tbody>
</table>

Ref. No:
[3]: Hedberg (1981)
[4]: Senge (1990)
[5]: Ulrich et al. (1993)
[6]: Nevis et al. (1995)
[7]: Weick and Westley (1996)
[8]: Tannenbaum (1997)
[9]: Goh and Richards (1997)

2.4 Organizational learning approaches

There are various existing approaches for OL which can be divided into “soft” and “hard” approaches. The “soft” side includes industrial engineering, on-the-job training, action research, organizational storytelling, and narrative simulation. The
“hard” approaches consist of e-learning, knowledge-based system (KBS), narrative database, and computational simulation.

2.4.1 Industrial engineering

Traditionally, industrial engineers measure learning by using learning curves (Yelle, 1979; Lieberman, 1987) or experience curves (Boston Consulting Group, 1968). Figure 2.10 shows an example of learning curve. Learning curves measure learning in terms of short-term manufacturing efficiency and cost. Besides studying experience curves, learning has also been measured by taking into account other variables such as number of patents (Decarolis and Deeds, 1999) or R&D expenditure (Bierly and Chakrabarti, 1996). Effective organizations use their experience to ‘tune’ the operations for doing the same work at a lower unit cost. Observers of aircraft manufacture in the 1930s noted that ‘as the quantity of units manufactured doubles, the number of direct labor hours it takes to produce an individual unit decreases at a uniform rate.’ (Yelle, 1979).

![Figure 2.10: An example of learning curve](image-url)
Unfortunately, the observed cost of reductions result from a complex mix of individual learning, technology changes, economies of scale, and changes in the management system (Dutton and Thomas, 1985). Thus, the internal structure and causation of organization-level learning curves are still poorly understood (Argote, 1993). Moreover, this approach measures the learning performance in terms of short-term results of individuals only. However, it ignores the other factors that can indicate the performance of learning and the long-term benefits of organization. It can only be applied to simple routine work rather than complex non-linear knowledge work. It focuses on how individuals learn only with limited support on OL (Uzumeri and Nembhard, 1998).

2.4.2 On-the-job training and e-learning system

The most typical way of learning is providing training for the workers. In the traditional model of on-the-job training, workers would typically receive a pre-prepared course in the new regulations, procedures, or processes to promote the new practices. E-learning systems are computerized systems in which the learner’s interactions with learning materials, instructors, and/or peers are mediated through technology. There are two models of e-learning which are: synchronous and asynchronous (Alavi and Leidner, 2001). A synchronous model resembles a classroom in which the instructor and the students are located in two or more remote locations. In the asynchronous model, students are provided with remote access to course material through information and communication technologies. It provides learners with great flexibility in choosing their own time, pace, frequency and form of learning activities (Alavi and Leidner, 2001). Companies are making asynchronous Web-based e-learning available to their employees in order to save the
travel expenses and loss of working hours associated with traditional classroom training (Alavi and Tiwana, 2003).

On-the-job training and e-learning systems are often conducted at locations that are different from their workplace and they are expected to apply the knowledge learnt later in their workplace. However, current theories of learning reveal that the knowledge acquisition process cannot be separated from the process of applying it (Landes et al. 1998). The effective integration of working and learning is a fundamental requirement for businesses to remain competitive.

Brown and Duguid (1991) also argue that learning is the essential bridge between working and innovation, and the three processes are inextricably intertwined. They argue that on-the-job training separates simplified abstract principles from the rich detail of actual practice and separates learners from the workplace community. Instead, they advocate that technology and business processes should support the existing learning practices within the workplace community by enabling individuals to somehow record and share their experience.

However, disappointing results are often observed as indicated by the data related to training effectiveness. Businesses spend up to US$100 billion per year to train up workers. It is interesting to estimate that less than 10% of this training transfers to the job (Detterman, 1993). Norman (2003) and Norman and Schmidt (2000) also presents a very interesting discussion of full-curriculum interventions versus small-scale laboratory studies. He concludes that curriculum-wide studies are not worth the effort involved in doing them. Lots of preparatory work is required for
on-the-job training. It is a costly, timely and labor consuming process.

2.4.3 Action research

Action research is a reflective process of progressive problem solving led by individuals working with others in teams to improve the way they address issues and solve problems (McNiff and Whitehead, 2006). It is a process of deep inquiry into one’s practices in service of moving towards an envisioned future aligned with values (Ogilvy, 2000). It is also a systematic, reflective study of one’s actions and the effect of these actions in a workplace context (Torbert, 2004). Action research tries new approaches and observes their effect on organizational processes and outcomes (Argyris, 1989). The effort has created a strong interest in helping employees to ‘learn how to learn’ (Argyris, 1982; Senge, 1990). Various groups of scholars have used systems analysis, case studies, and observation to find ways for companies to increase the rate of OL.

Action research aims at reflecting ones thinking and learning processes. The externalization of the thinking and learning processes is mental model. The idea of mental models is believed to be originated by the suggestion from Kenneth Craik (1943). He believed that the mind constructs “small-scale models” of reality that it uses to reason, to anticipate events and to underlie explanation. It is a model of the thinking process of how something works in the real-world.

Later, Johnson-Laird (1983) proposed that a mental model is a way of describing the process which humans go through to solve deductive reasoning problems. His theory included the use of a set of diagrams to describe various
combinations of premises and possible conclusions. He described the mental model as not necessarily wholly accurate, nor a complete match for what it models, but it is still useful as an aid to understanding (Johnson-Laird, 1983). He said that mental models are constructed from comprehension of discourse (Johnson-Laird, 1989).

Currently, mental models are used in various fields. They have different interpretations on the concept. In the cognitive sciences, a mental model is an internal scale-model representation of an external reality. It is built on-the-fly, from knowledge of priori experience, schema segments, perception, and problem-solving strategies (Oakhill and Garnham, 1996). A mental model contains minimal information. It is unstable and subject to change. It is used to make decisions in novel circumstances. A mental model must be “ runnable” and able to provide feedback on the results. Humans must be able to evaluate the results of action or the consequences of a change of state. They must be able to mentally rehearse their intended actions. This information can then be used to contribute to work on artificial intelligence (AI) and simulations (Markham, 1999).

From an organizational perspective, Senge (1990) describes mental models as deeply ingrained assumptions, generalizations or even pictures or images that influence how people understand the world. He goes on to assert that individuals’ knowledge, beliefs, experience and perceptions made up their understanding of their environment, which are affected by that person’s political, economic, social and cultural backgrounds. According to Vaudreuil (1995), consequently mental models are deeply ingrained assumptions, generalizations, and images that shape our thinking and influence on people actions. A mental model is a data processor which
determines how people use data to make decisions. Another stream of work has studied the economic impact of mid-level OL. They show how diversity in learning behavior can exert a complex influence on overall productivity (Meredith and Camm, 1989; Adler, 1990).

In action research, workers require training to reflect and externalize their thoughts. The success of OL heavily relies on the reflection abilities of the workers. Hence, it is timely, costly, and only a small number of people (mainly the managerial staff) are able to be involved in action research. Moreover, the concepts of action research are often too conceptual and theoretical. Focus is mainly on the cultural dimension which disregards the other organizational dimensions. It is difficult to find real-life examples and lacks critical analysis (Kerka, 1995).

2.4.4 Organizational storytelling

Narratives foster learning since they are easy to remember, easy to understand and deal with human-like experiences (Lämsä and Sintonen, 2006). Organizational theorists have now become much more aware that learning in organizations takes place through narrative knowledge (Czarniawska, 1998). According to Bruner (1991), people organize their experience and know-how in the form of narratives. By collecting stories in a particular organization, by listening and comparing different accounts, by investigating how narratives are constructed around specific events, by examining which events in an organization’s history generate stories and which ones fail to do so, people gain access to a deeper understanding of the organization and closely link to their experience (Gabriel, 2000). People can learn by studying the stories that people tell about each other and about the organization as a whole.
As mentioned by Rossiter (2002), narrative can also open windows into the cultural, political and emotional lives of organizations. It allows people to express deep and sometimes hidden or conflicting emotions. Narratives also stimulate people’s empathetic orientation which provides the basis for both cognitive and emotional responses to the experience and world-views of other people.

Researchers in organizational storytelling believe that the centrality of narrative is a fundamental structure of human sense making (Bruner, 1991; Polkinghorne, 1988; Ricoeur, 1991) and narrativity (i.e. interpretation of narrative) is central for OL (Czarniawska, 1998). Organizational storytelling makes use of narratives to recreate the circumstances of knowledge use. It recounts events in the form of a story within the context of an organization. The stories that people tell are a wonderful source of material for understanding culture and discovering examples of knowledge and learning (Brown, et. al, 2004). In recent years, a number of consultants (Boje, 2001; Gargiulo, 2005 and 2006) have turned to narratives as important means for enhancing organizational communication, performance and learning, as well as the management of change.

Similar to action research, organizational storytelling requires the story tellers to have good techniques in telling stories. The formation of a story is labor-intensive, time-intensive and cost-intensive. Moreover, some academics (Gabriel, 1991, 1995 and 2000) also argue that contrived or manufactured stories tend to generate anti-stories, provoking cynicism, mistrust and ridicule.
2.4.5 Knowledge-based system (KBS)

2.4.5.1 The concepts of KBS

On the “hard” side of OL approaches, some research work (Chen et al, 2003) shows that there is little doubt that information technology (IT) has tremendous potential for facilitating and enabling OL. With the advancement of IT, KBS represents human knowledge in a computer system through the use of artificial intelligence (AI) techniques and methods (Wiig, 1997). It is an infrastructure and enabling technology for KM to support knowledge acquisition, sharing, aggregation, filtering, diffusion and production throughout the organization (Hendricks and Vriens, 1999).

KBS is used to provide support for decision-making (Antony and Santhanam, 2007; Holsapple and Whinston, 1996; Hine and Goul, 1998; Morrison, 1993; Jessup and Valacich, 1993; Stein and Zwass, 1995) and it is focused on linking organizational knowledge to organizations’ work and their business processes (Davenport and Prusak, 1998). On the other hand, users implicitly learn about concepts, rules, and principles that improve their knowledge structures when users interact with the system and are focused on task completion. (Antony and Santhanam, 2007). KBS has an impact on each level of organizational knowledge from individual, group, to the organizational level (Dutta, 1997).

A schematic diagram of a typical KBS is shown in Figure 2.11. The core components of KBS are knowledge-base and inference/reasoning mechanisms (Huang, 2008). The valuable knowledge that resides within individuals is identified and disseminated throughout the organization (Tan and Platts, 2004). The knowledge
The acquisition module assimilates the experience of workers and stored in the knowledge repository in a certain format or schema. Moreover, the repository stores the knowledge invoked in prior decisions and retains the rules, policies and standard procedures of an organization (Hine and Goul, 1998). The knowledge inference module makes use the knowledge stored to deduce the solution to a problem (Chau and Albermani, 2002).

![Figure 2.11: A schematic diagram of a typical knowledge based system](image)

2.4.5.2 The applications of KBS

KBS has been widely applied to various studies and issues, including performance assessment (Ammar et al., 2004; Wang, 2005; Wang et al., 2007a), commercial loan underwriting (Kumra et al., 2006), logistics strategy design (Chow et al., 2005), farm productivity (Pomar and Pomar, 2005), mergers and acquisitions (Wen et al., 2005a and 2005b), defense budget planning (Wen et al., 2005a and 2005b), earthquake design (Berrais, 2005), system dynamics (Yim et al., 2004), conveyor equipment selection (Fonseca et al., 2004), customer service management (Cheung et al., 2003), etc.
For example, Wang et al. (2007a) proposed an assessment framework (DSSPE) for evaluating state-owned enterprises (SOEs) using DEA models, including a database management subsystem, a model base subsystem, a knowledge acquisition subsystem, and a dialogue subsystem. Cheung et al. (2003) proposed the multi-perspective KBS incorporates various AI technologies to achieve knowledge acquisition, knowledge diffusion, business automation and business performance measurement so as to drive the continuous improvement of the customer service quality. Chow et al. (2005) proposed the knowledge-based system (KLSS), which has been demonstrated to be suitable for application in the Hong Kong/Pearl River Delta region, which enhances the effectiveness of logistics strategy formulation by integrating techniques such as data warehousing, on-line analytical processing, multi-dimensional database management and case-based reasoning.

Although KBS provides an efficiency way to retrieve the information and knowledge, it has limited supports on creating new knowledge and motivating workers to learn (Chen et al, 2003; Barrett et al, 2004). By providing previous experience for problem solving, KBS may hinder innovation, which is insufficient to cope with the complex, diverse and continuously evolving business environment. Moreover, most of the KBSs are dealing with structural knowledge, in which narrative knowledge has received relatively little attention.

2.4.6 Narrative database

Recently, there is a new kind of KBS called narrative database which aims at retention, reuse and analysis of the narrative knowledge within an organization. It may be considered as a hybrid approach between the KBS approach and the
narrative approach. This stream is led by David Snowden. Snowden (2002b) mentions that we are now entering a new age of KM in which there is a new focus on the management of narrative. He argued that traditional storytelling methods are time consuming and often results in the loss of experiential knowledge (Snowden, 2000b). He states that it is easier, more natural and less onerous to capture narratives. Narrative databases not only allow people to capture large volumes of narrative material at low cost, but also critically, allow people to index those records on a single screen to give existing and new staff access to “the wisdom of the elders” for decision support (Snowden, 2002b). It provides a landscape of the narrative material based on the indexes. Figure 2.12 depicts an example of landscape of narratives in school parties (Snowden, 2008). The x-axis is degree of diversity (homogenous to heterogeneous). The y-axis is the degree of conflict (refusing to cooperate). The z-axis is the degree of stability.

A broad range of techniques is proposed (Snowden, 2000b) to manage the narratives and for direct observation of people in their work environment. Narrative databases allow abstract searches by archetypes, themes, intention, emotional level and perspective in such a way that multiple stories are encountered from which the listener can synthesize their own interpretations. Narrative databases also create a supporting “worse cases system” in which encountering stories of failure are more likely to foster success in the future (Snowden, 2000c).

Compared to traditional storytelling methods, narrative databases provide a radical, comparatively cheap, quick and effective solution for managing narrative knowledge and creating learning repositories. However, a narrative database offers
limited decision support for problem solving. It provides similar stories to the workers only, but without any recommendations or suggestions. The process of knowledge creation is also limited by just relying on workers’ making sense of the previous stories.

Figure 2.12: Landscape of narratives (Snowden, 2008)

2.4.7 Computational simulation

Due to the complexity and dynamicity of OL, a group of scholars (Carley, 2002b; Ouksel and Vyhmeister, 2001; Chen et al, 2002; Wong and Burton, 2000) believe that OL cannot be fully addressed by traditional techniques. They are turning to computational analysis by using computational models, generating findings computationally and doing computational simulation. A computational model for
testing OL theories contains a number of benefits which are cost effective, faster, flexible and ethical, etc. It can run a larger number of virtual experiments, with more cases per cell, larger virtual experiments. It can run faster than real-time. It can test a basic theory that needs to examine behavior in extreme conditions such as behavior in a space station, or under terrorist attack (Carley, 2002b). In the present study, computational organization simulations are classified into system dynamics, multi-agent simulations and knowledge-based simulations.

2.4.7.1 System dynamics

System Dynamics was founded in the late 1950s by Jay W. Forrester (Forrester, 1961). Unlike traditional scientists, who study the world by breaking it up into smaller and smaller pieces, system dynamics looks at things as a whole. It is an approach to understanding the behavior of systems over time. Its central concept is to understand how all the objects in a system interact with one another. It is claimed that, because there are often properties-of-the-whole which cannot be found among the properties-of-the- elements, in some cases the behavior of the whole cannot be explained in terms of the behavior of the parts.

System Dynamics deals with internal feedback loops, stocks, flows, and time delays that affect the behavior of the entire system. These elements help to describe how simple systems behave in a complex nonlinear way. A system can be anything from a steam engine, to a bank account, to a basketball team. The objects and people in a system interact through feedback loops which have many circular, interlocking, sometimes time-delayed relationships among its components.
Figure 2.13 shows an example (Senge, 1990). A “+” sign indicates that an element can increase the other element while a “−” sign indicates that an element can decrease the other element. The “(+)” is a signal that the loop is a reinforcing loop while the “(−)” is a signal that the loop is a balancing loop. There is also a “||” sign to indicate some time delay that it takes for the action to change the current state. In this example, Pesticide application decreases the number of insect A, so that the number of insect A damaging crops is reduced. However, as time goes on, the number of insect B increases due to the decreased number of insect A. As a result, the number of insect B damaging crops is increased. Figure 2.14 shows a system dynamics diagram created by a system dynamics software, NetLogo (NetLogo, 2008), for modeling wolf sheep predation.

By adopting system dynamics, people can observe how a change in one variable affects other variables over time, which in turn affects the original variable, and so on. It attempts to understand the basic structure of a system, and thus its behavior is understood. Many of these systems and problems being analyzed can be built as
models on a computer. System dynamics takes advantage of the fact that a computer model can be of much greater complexity and can carry out more simultaneous calculations than the human mind. Applications of system dynamics can be found in a wide range of areas such as the investigation of the impact of alternative policies for population, ecological, economic systems and product development (Repenning, 1999 and 2001, Sterman, 2000 and 2001).

Figure 2.14: A system dynamics diagram for wolf sheep predation (NetLogo, 2008)

2.4.7.2 Multi-agent simulation (MAS)

In contrast to system dynamics, MAS utilizes the dispersion and parallelism of computing technology. The concept originates from the real-world where many cases are inherently distributed in space, function, knowledge, expertise or information (Durgee et al, 1989). A number of intelligent agents, representing the real-world parties, cooperate or compete to reach the desired objectives designed by
their owners. These agents act collectively and collaborate to achieve their own individual goals as well as the common goal of the society to which they belong. It enables the ensemble to function beyond the capabilities of any singular agent in the set-up (Nwana and Ndumu, 1999).

The capability of a singular agent is limited by its knowledge, computing resources, and perspectives. If a problem domain is particularly complex, large, or dynamic, then the only way it can be reasonably addressed is to develop a number of functionally specific and modular components (agents) that specialize in solving a particular problem. This decomposition allows each agent to use its best knowledge for solving the particular problem (Jennings, 1999; Nwana, 1996). When interdependent problems arise, the agents need to coordinate or collaborate with one another to ensure that interdependencies are properly managed.

Russell and Norvig (2003) summarized the strength of MAS as consisting of three aspects. First, agents are intrinsically distributed. Their properties such as parallelism, robustness, and scalability make them well suited for domains which require resolution of interest and goal conflicts, integration of multiple knowledge sources and resources, time-bounded processing of very large data sets, or on-line interpretation of data arising from different geographical locations. Second, they are in accordance with the insight gained in discipline such as AI, psychology, and sociology that intelligence is tightly and inevitably coupled with interaction. Third, the modularity of agents makes it natural to encapsulate humans as peer agents to computer processes using common language and protocols to integrate people and machines. In nature, this integration requires people to reduce the bandwidth of their
A number of MAS have been developed such as Stella II (Peterson, 1993), PowerSim (Davidsen, 1994), Microworld Creator (Diehl, 1994), Vensim (Eberlein and Peterson, 1994), OrgAHead (Carley, 2002a), Construct-O (Carley, 2002a), an evolutionary computer model (Chen et al, 2002), etc. Figure 2.15 depicts the details for agents, activities, and decision task in OrgAHead (Carley, 2002a). It tries to simulate how an organization carrying out decision making process. The information is reduced to a sequence of ones and zeroes. Each agent receives information from a resource whether that resource is a task or another agent. It compares its information and answers to its superiors based on which answer, of either yes or no, allowed the organization to perform well before. The final decision makers, CEOS, provide the final and single organizational answer. If this answer corresponds to the real answer for the task vector, then all the agents receive positive feedback. Otherwise, they receive negative feedback and are less likely to answer the same way when they see the same set of information.

They are useful to provide a virtual world that predicts the effect of organization or team structure (Carley, 2002a; Ouksel and Vyhmeister, 2001), policy (Chen et al, 2002), theory (Stabler and Ewaldt, 1998), and characteristic (Okada et al, 1999; Wong and Burton, 2000) on the performance. They predict the effect of process routine and workflow and predict the effect of inter-organizational, virtual enterprise (e.g. Wong and Burton, 2000), supplier (e.g. Peli and Bart, 1997), and customer relations.
2.4.7.3 Knowledge-based simulation

The convergence of the representation based methods used in artificial intelligence (AI) and simulation has originated the emergence of knowledge-based simulation. The objective of this approach is to achieve more powerful and understandable simulations, which allows the simulation developers to construct, validate, develop and maintain simulations that can model a wider range of complex systems and particularly those that involves some elements of human decision making (Rothenberg, 1989). Instead of pure computational manipulation, knowledge-based simulation allows users to interact with the simulation in order to achieve a greater comprehension of the modeling phenomenon.

At the early development of knowledge-based simulation, it is used for
gathering information and problem-solving. For example, Fax et al (1989) proposed a knowledge-based simulation to simulate production planning and the utilization of machines with the aim of minimizing the inventory. It assists the user in the selection of key variable changes to achieve the simulation goals and obtains the optimum system configuration (Durán and Rosanna, 1998).

Currently, more and more knowledge-based simulations aim at educating or training people when they are playing games. For example, Anderson and Morrice (2000) developed a simulation game for supply chain service staff and for illustrating the impact of demand fluctuation as well as capacity adjustment. The concept of the beer game was first introduced in the 1960s. It illustrated the inventory problem of supply chain management.

![Figure 2.16: A screenshot of a web based beer game (Simchi-Levi et al, 2003)](image)

Simchi-Levi et al (2003) adapted the beer game to educate students in the
Chapter 2 Literature Review

concepts of supply chain management such as lead time reduction, global information sharing and centralized management. Figure 2.16 shows a screenshot of a web based beer game. The players can choose to be one of the supply chain parties such as a retailer, a wholesaler, a distributor or a manufacturer at the start of the game. During the game, the player is responsible for placing and ordering, and looks at the impact of their decisions on inventory and lead time.

2.4.7.4 Limitations of computational simulation

Although computational simulation provides some insights to model organizations, the simulation models are always over-simplified and abstract, and they are only able to simulate simple and linear work (Wang et al., 2006). Most of the simulations have identical characteristics which show a lack of consideration for the uniqueness of individuals. Moreover, relatively little research work has been found on the validation and the linkage to real data. Over-simplified computational models are fed with invalid and insufficient inputs. As a result, they come out with questionable results and conclusions (Wang et al., 2006).

2.4.8 Narrative simulation

In storytelling, some researchers (Cole, 1997; Cole et al, 1998; McCrary and Mazur, 1999; Morgan et al, 2002) integrate narrative with simulation, which develops 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. By interacting in small groups, participants reveal to each other their wisdom, attitudes, beliefs, knowledge, and misconceptions as they
proceed to resolve the simulated event.

Figure 2.17: A screenshot of narrative simulation on farm safety (National Agricultural Safety Database, 2002)

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). Figure 2.17 shows a screenshot of a narrative simulation on farm safety. Narrative simulation has advantages over full-scale field simulations or even participation in actual events. First, narrative simulation is usually carried out in less time and with less expense than a full-scale field simulation. Second, errors made during a narrative simulation may be embarrassing but are not dangerous. Similar errors in a full-scale field exercise, or during an actual event, could be fatal. Third, narrative simulations can be constructed to foreshorten a long
period of time. A real situation that might develop and be resolved over a few days or a few months can be simulated and discussed within an hour.

However, the methods of narrative collection are labor-intensive, timely and costly. The quality and time for constructing narrative simulation are heavily reliant on the experience of the simulation designer (Wang et al., 2006). There is a need to automate the process of narrative collection and construction of narrative simulation.

2.4.9 Limitations of Current Approaches for OL

Various approaches to the research into OL have discussed and most of them provide valuable insights for society. However, there are some limitations to the existing approaches. Table 2.4 summarizes the limitations of these approaches.

Table 2.4: Limitations of conventional approaches for organizational learning

<table>
<thead>
<tr>
<th>Approaches</th>
<th>Limitations</th>
</tr>
</thead>
</table>
| Industrial engineering | ● It measures the learning performance in terms of short-term results of individuals only, but it ignores the other factors that can indicate the performance of learning and the long-term benefits of organization. (Dutton and Thomas, 1985)  
                          ● It can only be applied to simple routine work rather than complex non-linear knowledge work.  
                          ● It is not concerned with knowledge creation, knowledge sharing and knowledge storing.  
                          ● It focuses on how individuals learn only, with limited support for OL. (Argote, 1993) |
| On-the-job training    | ● On-the-job training is often at a different location from the working place and workers are expected to apply the knowledge learnt later in their workplace. However, current theories of learning reveal that the knowledge acquisition process cannot be separated from the process of applying it. (Brown and Duguid, 1991)  
                          ● Lots of preparation work is required for on-the-job training. It is a cost, time and labor consuming process. (Detterman, 1993) |
| Action                 | ● The methods of knowledge acquisition and sharing are                         |
| **research** | labor-intensive, timely and costly.  
- It focuses on the learning in professional and managerial level which has a high risk that the success of OL relies heavily on the abilities of the managerial personnel only. (Kerka, 1995)  
- It requires highly experienced people for carry out the inquiries and research. (Kerka, 1995)  
- Knowledge retaining and storage are not adequately considered. Organization may suffer a loss when knowledgeable persons leave the company. |
| **Organizational storytelling** | The methods of story creation and collection are labor-intensive, timely and costly.  
- The quality and time for constructing narrative simulation are heavily reliant on the experience of the storyteller. (Gabriel, 1991, 1995 and 2000)  
- The knowledge sharing method based on face-to-face conversion is inconvenient and costly. |
| **KBS** | It creates an environment for storing and retrieving the past information and knowledge in an efficient way, but it provides limited support for creating new knowledge and motivating workers to learn. (Chen et al, 2003; Barrett et al, 2004)  
- It provides past information or cases for training and decision support, which is insufficient to cope with the complex, diverse and continuously evolving business environment. Such kind of systems may hinder innovation by providing previous experience for problem solving. (Chen et al, 2003; Barrett et al, 2004)  
- Narrative knowledge is not sufficiently taken into account. |
| **Narrative database** | It has limited decision support for problem solving. It provides similar stories to the workers only, but without any recommendations or suggestions.  
- The process of knowledge creation is also limited by just relying on the workers to make sense of the previous stories.  
- It aims at providing previous experience for problem solving, which may hinder innovation. |
| **Computational simulation** | The simulation models are always over-simplified and abstract, and they are able to simulate simple and linear work only. (Wang et al., 2006)  
- Identical characteristics are attributed to the individuals. This shows a lack of concern for the uniqueness of individuals.  
- Little research work has been done on validation and the linkage to real data.  
- Over-simplified computational models are fed with invalid and insufficient inputs and therefore they come out with questionable results and conclusions. (Wang et al., 2006) |
| **Narrative simulation** | The methods of narrative collection are labor-intensive, timely and costly.  
- The quality and time for constructing narrative simulation are heavily reliant on the experience of the simulation designer (Wang et al., 2006) |
Beside the items listed in the Table 2.4, there are also some common limitations of the existing approaches. Firstly, most of them ignore the value of diversity. It is argued that diversity, if managed well, increases innovativeness and creativity and improves decision making by providing many viewpoints on upcoming problems (Cox and Blake, 1991; Dowling et al, 1999; Jackson et al, 1993). For example, in industrial engineering, knowledge management systems, computational simulations, and narrative approach, the viewpoint of the system designer or manager provides the only perspective for the learning system. Secondly, the existing approaches apply past experience for solving new problems; there is lack of a proactive manner for dealing with future situations. Thirdly, no approach has a balance between the concern for narrative knowledge management, and at the same time providing a labor effective, cost effective and time effective method for narrative collection, analysis, reconstruction, and maintenance.

2.5 Technologies for OL

In order to achieve the facilitating factors for OL and overcome the limitations found in the existing methods, an effective and efficient method to collect, construct, analyze, share and reuse narrative knowledge within an organization is needed. Decision support functions to assist workers’ daily work are also required. The state-of-the-art of several technologies is reviewed in the present study to realize these objectives. They include automatic narrative generation, artificial intelligence (AI), and concept mapping.

2.5.1 Automatic narrative generation

Some researches have been conducted into computer-based text generation.
Early systems included interactive story segments where the system would produce part of the story and then wait for user interaction before producing more of the story like ZORK (Lebling et al., 1979). The user uses a text command to control the story, and the story state is relayed to the user via a text output. Some systems include initial conditions; or story syntax could be changed in order to produce brand new stories such as TALE-SPIN (Meehan, 1977) and UNIVERSE (Lebowitz, 1985). TALE-SPIN was a program that produced stories by setting goals for characters and then recording their attempts to reach the goals. It demonstrated how computer techniques in problem-solving can be applied to storytelling.

UNIVERSE (Lebowitz, 1985) focuses more on plot creation than event description. Figure 2.18 shows a story developed by UNIVERSE. It gives explicit values to a number of character attributes, both general and directed toward particular other characters, as well as a number of plot fragments whose preconditions are based on the values of attributes for different characters and whose post-conditions modify those attributes and generate events as side-effects. The plot fragments represent what the story author wants to happen, rather than the personal intentional goals of any particular character as in TALE-SPIN.

Figure 2.18: A story developed by UNIVERSE (Lebowitz, 1985)
They were successful in showing the ability of computers to generate very short coherent stories. However, they were only able to generate a limited range of stories with a rigid pre-defined structure. They are unable to reason about how to actually write stories with a variety of purposes, perspectives, and intended audiences instead of merely as English-based expansions of encoded rules with a single purpose, perspective, and audience.

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 a story that satisfies its grammar and is not able to modify its knowledge to generate different outcomes.

Current systems such as MINSTREL (Turner, 1993; Turner, 1994), MEXICA (Pérez, 1999; Pérez and Sharples, 2001) and BRUTUS (Bringsjord and Ferrucci 2000) are hybrid systems which consist of merging different known methodologies into one program. Figure 2.19 shows a story developed by BRUTUS. BRUTUS is built on a Prolog-based system, which allows defining frame-structures and relations between frames and production rules.

MINSTREL included a case-based reasoning (CBR) process to model the creative process of generating a story line. A story developed by MINSTREL is
shown in Figure 2.20. It develops stories by predefined schema themes known as Planning Advice Themes. When MINSTREL cannot find events in episodic memory to instantiate the theme, or all available events have been employed twice in previous stories, a set of heuristics called Transform Recall Adapt Methods (TRAMS) are employed to create novel scenes. It can only produce stories with four different themes, which are structurally predefined and which can only turn around a planning process.

Dave Striver loved the university. He loved its ivy-covered clocktowers, its ancient and sturdy brick, and its sun-splashed verdant greens and eager youth. He also loved the fact that the university is free of the stark unforgiving trials of the business world — only this isn’t a fact; academia has its own tests, and some are as merciless as any in the marketplace. A prime example is the dissertation defense: to earn the PhD, to become a doctor, one must pass an oral examination on one’s dissertation.

Dave wanted desperately to be a doctor. But he needed the signatures of three people on the first page of his dissertation, the priceless inscription which, together, would certify that he had passed his defense. One the signatures had to come from Professor Hart. Well before the defense, Striver gave Hart a penultimate copy of his thesis. Hart read it and told Striver that it was absolutely first-rate, and that he would gladly sign it at the defense. They even shook hands in Hart’s book-lined office. Dave noticed that Hart’s eyes were bright and trustful, and his bearing paternal.

At the defense, Dave thought that he eloquently summarized Chapter 3 of his dissertation. There were two questions, one from Professor Rodman and one from Dr. Teer; Dave answered both, apparently to everyone’s satisfaction. There were no further objections. Professor Rodman signed. He slid the tome to Teer, she too signed, and then slid it in front of Hart. Hart didn’t move, “Ed?” Rodman said. Hart still sat motionless. Dave felt slightly dizzy. “Edward, are you going to sign?” Later, Hart sat alone in his office, in his big leather chair, underneath his framed PhD diploma.

Figure 2.19: A story developed by BRUTUS (Bringsjord and Ferrucci 2000)

MEXICA is a computer model based on an engagement-reflection cognitive account of creative writing that produces stories about the México City. A story developed by MEXICA is shown in Figure 2.21. During the engagement-mode, the system produces material driven by the content and the rhetorical constraints avoiding the use of explicit goal-states or story-structure information. During the reflection-mode, the system solves the conflicts generated during engagement, satisfies coherence requirements, and evaluates the novelty and interest of the story in progress. If the results of the evaluation are not satisfactory, MEXICA can modify
the constraints that drive the production of material during engagement.

Once upon a time there was a lady of the court named Jennifer. Jennifer loved a knight named Grunfeld. Grunfeld loved Jennifer.

Jennifer wanted revenge on a lady of the court named Darlene because she had the berries which she picked in the woods and Jennifer wanted to have the berries. Jennifer wanted to scare Darlene. Jennifer wanted a dragon to move towards Darlene so that Darlene believed it would eat her. Jennifer wanted to appear to be a dragon so that a dragon would move towards Darlene. Jennifer drank a magic potion. Jennifer transformed into a dragon. A dragon moved towards Darlene. A dragon was near Darlene.

Grunfeld wanted to impress the king. Grunfeld wanted to move towards the woods so that he could fight a dragon. Grunfeld moved towards the woods. Grunfeld was near the woods. Grunfeld fought a dragon. The dragon died. The dragon was Jennifer. Jennifer wanted to live. Jennifer tried to drink a magic potion but failed. Grunfeld was filled with grief.

Jennifer was buried in the woods. Grunfeld became a hermit.

Recently, more researchers (Liu and Singh, 2002; Singh, 2002) 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 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, ProtoPropp, applied ontology of explicitly declared relevant knowledge and 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 screenshot of ProtoPropp is shown in Figure 2.22. The resulting story is generated as a sketch of a plot described in natural language by means of natural language generation (NLG) techniques.

![Figure 2.22: A screenshot of ProtoPropp (Gervás et al, 2005)](image)

To summarize, most of the previous research work appears to consist of predefined conditions, predefined goals, and inferred post-conditions. The resulting narratives are hence rigid and suffer from a lack of diversification. Moreover, the
top-to-bottom approach requires a large amount of work for constructing and maintaining the predefined elements. In the present study, a bottom-up and semi-automatic method for the collection of narratives is proposed. This helps to save time and reduce the cost for maintaining the knowledge update. Furthermore, the method automatically constructs the scenarios based on multiple narrative resources, in order to prevent simple and direct usage of previous narratives.

2.5.2 Artificial Intelligence (AI)

AI is the science and engineering of creating programs and systems that are intelligent (Poole, et al., 1998). There is no universally accepted definition of intelligence. Some researchers have suggested that the major idea of AI is that knowledge of people is encoded into knowledge representations (Luger and Stubblefield 2004; Nilsson 1998; Davis, et al., 1993). Knowledge representation is the format and method used to encode knowledge into the knowledge base of computational system (ACM, 1998; Russell and Norvig 2003). It can be natural language (Helbig, 2006), cases (Aamodt and Plaza, 1994), rules (Russell and Norvig 2003), scripts (Schank and Abelson, 1977), frames (Minsky, 1975), neural networks (Hertz, et al., 1990), semantic networks (Helbig, 2006), etc. Different knowledge representations and their inference mechanisms have been embedded into KBS for solving complex problems. AI approaches such as case-based reasoning (CBR), artificial neural networks (ANN), fuzzy logic and genetic algorithm (GA) are the key techniques for supporting OL (Laha and Mandal, 2008). In particular, computational intelligence (CI) is a successor of AI. It embraces techniques including fuzzy logic, ANN, and GA (Laha and Mandal, 2008).
2.5.2.1 Case-based reasoning (CBR)

CBR is a problem-solving approach that relies on past and similar cases to find solutions to new problems (Kolodner, 1993). It simulates human decision making processes and enables the accumulation of previous experience. A knowledge cycle consists of knowledge processes such as capture, distribution, and reuse. This is strongly correlated with the CBR cycle which includes retrieve, reuse, revise, and retain knowledge (Aamodt & Plaza, 1994). Hence, the strong association between the CBR cycle and KM’s knowledge cycles justify the consistent use of CBR to guide the design of KM systems (e.g., Cheung et al., 2003; Weber and Aha, 2003; Chow et al., 2005).

A case in CBR is specified by a set of attributes. This set of attributes is structured by the domain. Each case has a unique key and the case description. A new problem is solved by retrieving similar cases about similar situations from the knowledge repository (KR), reusing or revising the case in the context of the new situation, and retaining the new case in the KR (Aamodt & Plaza, 1994). One of the important advantages of CBR is its learning capability. Its problem-solving ability enhances with the increasing amount of accumulated cases. In the other words, its problem-solving ability is poor when there are few cases in the case base (Wang et al., 2007b).

Therefore, CBR is some kind of experience mining (Richter, 2008). The approach has been extended to more general situations where experience is retained. Major examples are the “experience factory” (Althoff et al., 1998) and the technique of “lessons learnt” (Weber et al., 2001). CBR has also been widely used in various
studies and issues, including medical and the clinic industry (Koton, 1988; Casanova and Micarelli, 1995; López and Plaze, 1997; Zhang et al., 1999; Frize and Walker, 2000; Jain and Marling, 2001; Hsu and Ho, 2004; Trivedi et al., 2004; Chang, 2005), mental health (Ferns, 1995; Wang et al., 2007b), logistics (Chow et al., 2005; Cheung et al., 2005a and 2006), education (Chu et al., 2008), physical asset management (Wang et al., 2005) and customer service management (Cheung et al., 2003). More examples can be found in the paper of Schmidt et al (2001).

A number of systems have been built based on the CBR approach for achieving OL (e.g. Perner, 2007; Weber et al., 2001; Hine and Goul, 1998). Perner (2007) applied CBR for detecting novelty inside a knowledge repository and used it as an inference engine. Weber et al. (2001) have investigated the use of different intelligent techniques to support organizational knowledge sharing efforts. They concluded that CBR is a suitable technology for storing knowledge learned from experience for future reuse.

Another important advantage of CBR is its learning capability (Weber and Aha, 2003). Its problem-solving ability improves with the increasing amount of accumulated cases. By adopting CBR, organizations are able to deal with new problems by referring to their past knowledge more effectively (Weber and Aha, 2003). However, the problem-solving ability is poor when there are few cases in the case base (Wang et al., 2007b). It should be incorporated with other technologies to increase its problem-solving ability (Bichindaritz et al, 1998; Phuong et al, 2001).
Fuzzy logic has been proven to be a powerful tool for building intelligent systems (Von Altrock, 1997). The term “fuzzy logic” emerged in the development of the theory of fuzzy sets by Lotfi Zadeh (1965 and 1968). Fuzzy set theory deals with reasoning that is approximate rather than precisely deduced from classical logic. It is a way of processing data by allowing partial set membership rather than crisp set membership. A fuzzy subset \( X \) of a crisp set \( Y \) is characterized by assigning to each element \( y \) of \( Y \) the degree of membership of \( y \) in \( X \) (e.g., \( Y \) is a group of people, \( X \) is the fuzzy set of old people in \( Y \)). \( Y \) is a set of propositions the elements of which may be assigned a degree of truth, which may be “absolutely true,” “absolutely false” or some intermediate truth degree. It provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information (Orchard, 1994). It has proven to be an excellent choice for many control system applications since it mimics human control logic (Lou and Huang, 2003). The concept for dealing with uncertainty is highly suited to the problems that are found in organizations (Laha and Mandal, 2008).

Fuzzy logic incorporates simple IF-THEN rules with fuzzy variables such as output temperature and fuzzy terms such as very hot, fairly cold, probably correct, to solve control problem rather than attempting to model a system mathematically. It is empirically-based, relying on an operator's experience rather than their technical understanding of the system. For example, terms like "IF (process is too cool) AND (process is getting colder) THEN (add heat to the process)" or "IF (process is too hot) AND (process is heating rapidly) THEN (cool the process quickly)" are used (Negnevitsky, 2002).
Fuzzy logic is mainly applied in OL for decision support (e.g. Borges and Antunes, 2003; Liu and Lai, 2008; Mikhailov and Madan, 2003). Borges and Antunes (2003) proposed a decision support model for energy-economy planning by using fuzzy logic. Liu and Lai (2008) proposed an integrated decision-support framework that employs fuzzy logic to manipulate subjectivity as decision makers do in appraising the facts and values.

Experts use natural language to express the required information, by means of a number of IF/THEN fuzzy rules, facilitated by the use of linguistic variables within their syntax (Gravani et al., 2007). The major advantage of the FL concept is that it manages to transform this information from the linguistic to a background analytical level, where mathematical computations take place (Gravani et al., 2007). The concept of fuzzy logic for dealing with linguistic variables is eminently suited to the problems that found in organizations. However, the applications of fuzzy logic in narrative simulation have received relatively little attention.

2.5.2.3 Artificial neural networks (ANN)

In general, machine learning involves adaptive mechanisms that enable computers to learn by example and analogy. Artificial neural network (ANN) is one of the most popular approaches in machine learning (Russell and Norvig 2003). As shown in Figure 2.23, ANN is characterized by arrays of highly interconnected cells, often arranged in layered structures, where each cell, or neuron, is roughly similar to the next (Negnevitsky, 2002). Each neuron has an adjustable weight factor associated with it and it is connected to all other neurons in the adjacent layer.
through these weighted connections (Kim et al., 2003). It provides the desired changes of parameters based on what the network has been trained on.

![Diagram of typical ANN](image)

**Figure 2.23: The architecture of typical ANN**

Intrinsically, a sufficient amount of data sample is a key factor in order to obtain accurate feedback from the trained network. The network can learn the relationships between data sets by simply having sample data represented to its input and output layers (Negnevitsky, 2002). The training of the network with input and output layers mapped to relevant realistic values develops the correlation between these two groups of data. Among neural networks, multilayer perception (MLP) regression with an error back-propagation is commonly used (Haykin, 1999). Multilayer perceptions have been applied to solve some difficult and diverse problems by training them in a supervised manner with an error back-propagation algorithm. This algorithm is based on the error-correction learning rule. The error back-propagation algorithm consists of two passes through the different layers of the network: the forward pass and the backward pass (Haykin, 1999).
Chapter 2 Literature Review

Forward pass is defined as:

\[ V_j(n) = \sum_{i=0}^{m} W_{ji}(n)X_i(n) \]  \hspace{1cm} (2.1)

where \( m \) is the total number of inputs applied to neuron \( j \), \( W_{ji}(n) \) is the synaptic weight connecting neuron \( j \) to neuron \( i \), and \( X_i(n) \) is the input signal of neuron \( j \).

Backward pass is defined as:

\[ W_{ji}(n) = \alpha \Delta W_{ji}(n-1) + \eta \delta_j(n)Y_j(n) \]  \hspace{1cm} (2.2)

where \( \alpha \) indicates momentum constant which controls the feedback loop acting around \( \Delta W_{ji}(n) \), \( \eta \) indicates learning rate, and \( \delta_j(n) \) indicates local gradients that adjust the synaptic weights of the network.

ANN is applied in organizational problems for inference (e.g. Kuo and Chen, 2004; Kuo et al., 2001). Kuo and Chen (2004) built a decision support system for order selection in electronic commerce based on ANN. Kuo et al. (2001) proposed an intelligent stock trading decision support system to formulate the knowledge base of fuzzy inference rules which can measure the qualitative effect on the stock market.

The cause and effect relationships of inputs (reasons) and outputs (conclusion/results) in ANN are implicit (Dutta et al., 2004) and the relationships are represented by the adjustment of weighting on the variables. However, the explicit meanings and relationships between the inputs and outputs are essential to the organization in OL (Nonaka and Konno, 1998).
2.5.2.4 Genetic algorithm (GA)

GAs (Fogel 1966; Rechenberg, 1973; Holland 1975; Goldberg, 1989) are a group of evolutionary algorithms, that use the evolution principle that was originally proposed by Darwin (1859). It is often applied to search, design, and combinatorial optimization problems (Mantere and Alander, 2005). GA forms a kind of electronic population that mimics the fight for survival, adapting as well as possible to its environment. Surviving and crossbreeding possibilities depend on how well individuals fulfill the target function. Solutions are selected from the population based on their fitness for their function, and are modified based on recombination, or randomly mutated to form a new population. The new population is then used in the next iteration of the algorithm until a satisfactory solution is reached.

Figure 2.24 shows how the GA operates. At first, it creates an initial population, e.g. by a random number generator or by supplying known good solutions. The initial population is then evaluated against the fitness function. Then the population is tested with the termination conditions. A termination condition can be that a solution is fit enough or a given number of trials has been evaluated. If the termination condition is not satisfied, iteration continues by selecting high fitness parents to generate new offspring by crossover and mutation operations. The new individuals are then tested by the fitness function (Mantere and Alander, 2005).

The GA performs well when dealing with well-defined optimization problems and provides decision support based on the optimization results (Mantere and Alander, 2005). A lot of research work has been done on optimizing the parameters of algorithms, such as CBR, fuzzy logic and ANN. For example, Hochman et al.

![Figure 2.24: A schematic diagram of genetic algorithm](image)

2.5.3 Data mining

Data mining has a basic assumption that valuable information is embedded in large volumes of data (Fayyad and Uthurusamy, 1996). Data mining is a technique for uncovering such information. It automatically searches for unknown correlations in the data by looking for interesting patterns and clusters (Loeb et al., 1998; Klosgen and Zytkow, 2002). There are different data mining techniques, but almost all of them can be classified into three groups: clustering and classification; association rule mining; and text mining (Romero and Ventura, 2007).
Clustering and classification

Clustering is a process of grouping physical or abstract objects into classes of similar objects. Clustering and classification are both classification methods (Klosgen & Zytkow, 2002). Clustering is an unsupervised classification of data into groups (called clusters) so that data points within a cluster are more similar to each other than to data points in other clusters (Jain et al., 1999). The term unsupervised stands for the fact that there is no a priori knowledge about the partition of data. In a more formal definition, a clustering \( C_i \) is the partition of a data set \( D \) into sets \( C_1, C_2, ..., C_k \) called cluster such that \( C_i \cap C_j = \emptyset \) and \( \bigcup_{i=1}^{k} C_i = D \).

Classification is supervised classification and it is also related to prediction (Romero and Ventura, 2007). Classification predicts class labels (Olson and Shi, 2005), whereas prediction predicts continuous-valued functions. Decision trees (DTs) are commonly used for classification since they are easily understandable. It was first introduced by Hunt et al. (1966). According to Mitchell (1997), DTs are used to classify instances by sorting them down to the tree form and to the root or to some leaf node, which provides the classification of the instance. Each internal node of the tree specifies a test on some attributes of the instance with regard to some of its value, and each branch descending from that node corresponds to one of the possible values of this attribute.

Talavera and Gaudioso (2004) use clustering to discover patterns reflecting user behaviors. They propose models for collaboration management to characterize similar behavior groups in unstructured collaboration spaces. Damez et al. (2005)
use a fuzzy decision tree for user modeling and for automatically discriminating between a novice and an experienced user. They use an agent to learn the cognitive characteristics of a user’s interactions and classify users as experienced or not.

2.5.3.2 Association rule mining

Association rule mining is one of the most well studied mining methods (Romero and Ventura, 2007). Such rules associate one or more attributes of a dataset with another attribute, producing an if–then statement concerning attribute values. Mining association rules between sets of items in large databases was first introduced by Agrawal et al. (1993). The original problem was the market basket analysis that tried to find all the interesting relations between the products that were bought. It is defined as follow: Let $D$ be a database of transactions, where each transaction consists of a set of distinct items $I$, called itemsets. An association rule is a implication of the form $X \rightarrow Y$ where $X \subseteq I$, $Y \subseteq I$ and $X \cap Y = \emptyset$. The rule is associated with a support $s$ and a confidence $c$. The rule $X \rightarrow Y$ is said to have support $s$, if $s\%$ of the transactions in $D$ contain $X \cap Y$, whereas it is said to have confidence $c$, if $c\%$ of the transaction in $D$ that contain $X$ also contain $Y$. The association mining rule first calculates the set of frequent itemsets, and then it used the itemsets to extract the association rules.

Examples can be found in Lu (2004), where he uses association fuzzy rules in a personalized e-learning material recommender system. He uses fuzzy matching rules to discover associations between the student’s requirements and a list of learning materials. Feng et al. (2004) use association rules to guide a search for best fitting transfer model of learning in intelligent tutoring systems. The association rules
determine what operations to perform on the transfer model that predict a learner’s
success. Yu et al. (2001) modify traditional web logs, and apply fuzzy association
rules to find out the relationships between each pattern of a learner’s behavior;
including the time spent online, number of articles read and number of articles
published, number of questions asked, etc.

2.5.3.3 Text mining

Text mining methods can be viewed as data mining extended to text data. It is
an interdisciplinary area involving machine learning and data mining, statistics,
information retrieval and natural language processing (NLP) (Grobelnik et al., 2002).
Text mining can work with unstructured or semi-structured datasets such as full-text
documents, HTML files, emails, etc. NLP techniques are commonly used as the first
step in text mining for converting the unstructured text into a structural format
(Milic-Frayling, 2005), and then other data mining techniques can be applied to
retrieve interesting patterns.

In general, text processing starts with tokenization processes which identify
word and sentence boundaries. Common methods are finite-state machines (Hopcroft
and Ullman, 1979; Wang et al., 2008a) and mutual information (Church et al., 1991;
Church and Hanks, 1989). Finite-state machines use simple heuristics for identifying
word boundaries. It assumes that the characters of a text are processed in sequence
and when a character other than a letter, a digit, or a hyphen is encountered, it
identifies the token boundary. It is simple, but a related problem involves
discovering collocations (Milic-Frayling, 2005). Collocations consist of multiple
words whose collective meaning is sufficient and should not be further decomposed.
Mutual information is a method to find collocations in text by considering word bigrams (2 words), trigrams (3 words) or n-grams, and by analyzing their frequency in a corpus of text (Church et al., 1991; Church and Hanks, 1989).

After tokenization, disambiguation is applied to solve the morphological variances. The most common method is stemming (Harman, 1991). Stemmers use a dictionary of common word endings for looking up the word which is presented for stemming. For example, “factories” is stemmed as “factory” based on the rule “If ‘ies’ but not ‘eies’ or ‘aies’ then ‘ies’ → ‘y’”. Part of speech (POS) tagging is then applied for assigning the POS to each word in a sentence. One of the common approaches in POS tagging is transformation-based tagging (Brill, 1995; Roche and Schabes, 1995). Firstly, the text is tagged by a simple word lookup in a lexicon. Then transformation-based tagging is applied to correct the tagging error by rules. Table 2.5 shows an example of an error-correcting rule. The rules are learnt automatically from a training corpus. The level of sentence analysis depends on the application. Parsing is often applied to discover sentence structure by identifying the phrases, such as subject, object, and predicate (Milic-Frayling, 2005).

Table 2.5 Example of an error-correcting rule

<table>
<thead>
<tr>
<th>Initial tag</th>
<th>Final tag</th>
<th>Triggering condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>NN</td>
<td>VB</td>
<td>Previous tag is TO</td>
</tr>
<tr>
<td>Singular or mass noun</td>
<td>Verb, base form</td>
<td>Previous word it to</td>
</tr>
</tbody>
</table>

Example:
We need to map the region carefully. map (NN) to map (VB)

In application of text mining to OL, Tane et al. (2004) use text mining and text clustering techniques for grouping documents according to their topics and similarities so as to provide better document retrieval. Hammouda and Kamel (2005)
propose performing data mining on documents, which serves as a basis for knowledge extraction in e-learning environments. In the process of text mining, a clustering approach is employed to identify groups of documents. Dringus and Ellis (2005) propose using text mining as a strategy for assessing asynchronous discussion forums. It improves the educator’s ability to evaluate the progress of a thread discussion. Text mining is an important technology for analysing natural language text. However, current applications seldom apply data and text mining on mining narrative data; neither have they been used in narrative simulation.

2.5.4 Concept mapping

In order to manipulate narrative knowledge, it is necessary to convert the unstructured narrative text into a structural format, which can be easily processed by computers. In the present study, a concept map is considered due to its simple structure as well as its capability to represent and infer narrative knowledge.

Concept maps have their roots in their relationship to memory and learning theory. The concept was developed in 1972 in Novak’s research program (Novak, 1990; Novak & Musonda, 1991). This program was based on the learning psychology of David Ausubel (1963 and 1968; Ausubel et al, 1978). The fundamental idea in Ausubel’s cognitive psychology is that learning takes place by the assimilation of new concepts and propositions into existing concepts and propositional frameworks held by the learner. This knowledge structure as held by a learner is also referred to as the individual’s cognitive structure. Semantic memory theory believes that knowledge is stored in a network format where concepts are connected to each other (Collins and Smith, 1988). The more tightly interconnected
the knowledge representation, the more likely it is that a person recalls information at the appropriate time. As a result, a network representation can be used to show the integration of different concepts.

Based on Novak & Cañas (2006), the concept map is a graphical tool for organizing and representing knowledge. Knowledge is graphically displayed as a network of nodes and links. A concept is defined as a perceived regularity in events or objects, or records of events or objects. A proposition is defined as statement about some object or event in the universe, either naturally occurring or constructed. Propositions contain two or more concepts connected using linking words or phrases to form a meaningful statement. Figure 2.25 shows an example of concept map. There are 4 propositions in the concept map: (Concept Map consists of Concepts), (Concept Map consists of Relations), (Concepts denoted by Nodes), (Relations denoted by Links). The labeling of nodes contains the concepts. The labeling of the link provides information about the nature of the relationship between the two concepts.

![Figure 2.25: An example of concept map](image)

Several research studies have developed different methodologies to extend the
usage of concept maps. Lin et al (2002) introduce a concept map focusing on propositions with weights, which is named the “weighted concept map.” Chen et al (2001) proposed an extended concept map called an attribute concept map (ACM). ACM associates its concept nodes and relation links with attribute values which indicate the relative significance of concepts and relationships in knowledge representation.

Figure 2.26 shows a concept map created by a concept map tool, CmapTools (CmapTools, 2008). Concept maps have been used as advance organizers (Willerman and Harg, 1991), assessment tools (Gouli et al, 2004), cooperative learning tools (Boxtel et al, 1997), human-machine interfaces design (Herl et al, 1999; McClellan et al, 2004), and communication tools for organizing ideas and promoting problem solving strategies (Okebukola, 1992). The theory has resulted in different terms being used to describe concept maps including semantic networks (Mularz and Lyell, 2004, Fisher, 1990) and knowledge maps (Herl et al, 1999).

![Figure 2.26: A concept map created by a concept map tool (CmapTools, 2008)](image-url)
The construction of a concept map consists of enumerating a list of concepts and determining the linking phrases that should connect the concepts to form meaningful propositions. Appropriate word selection, both for concepts and linking phrases, is the key for an accurate knowledge representation of the user’s understanding of the domain. Prior research of word selection is summarized into three categories which are dictionary (Braam et al, 1991; Callon et al, 1991; Zitt & Bassecoulard, 1994), statistical (Cutting et al, 1992; Eisen et al, 1998; Karypis et al, 1994), and linguistic approaches (Rajaraman K. et al, 2002; SanJuan & Ibekwe-SanJuan, 2006).

The dictionary approach utilizes a dictionary, which contains the forms, meanings and relationships between words and phrases. By matching the dictionary with the words of sentences in each article, the concepts in the article are extracted. Relationships between the concepts are then coordinated based on the dictionary. For example, Alves et al. (2002) use WordNet to extract an initial hierarchy of nouns from a document to build an initial list of concepts, followed by several user feedback iterations to deduce relationships between pairs of concepts and hypothesize about their relations. The major advantages of this approach are its efficiency of execution and ease of implementation. However, the prior keyword list is external to the documents. It reflects a general understanding of the domain instead of the intention of the document author. Since words in the target articles do not consist of new words, it requires further operations for handling these new words.
In the statistical approach, words are selected based on term weighting indices such as Inverse Document Frequency (IDF) or Mutual Information (MI). Feldman et al. (1998) have proposed a system for extracting terms and computing associations between them to display a context graph. The context graph primarily uses numerical strengths to capture the relation terms. Semio Map (Semio, 2008) and TextAnalyst (Megaputer Intelligence, 2008) (see Figure 2.27) are some of the other systems that can create graphs based on term correlations. This approach eliminates the low frequency words so as to reduce the number of words being extracted. However, this also results in the drastic elimination of more than half of the initial data from the analysis. Moreover, Price and Thelwall (2005) have demonstrated the usefulness of low frequency words for scientific Web intelligence (SWI). Removal of low frequency words results in documents becoming more general and similar.

The linguistic approach uses semantic knowledge bases, heuristics, or rules to extract concepts. Paik et al. (2001) define a representation called Concept-Relation-Concept (CRC) triples. Their system analyzes raw text to construct a database of CRC triples based on semantic relations. However, it is hard to make linguistic generalizations from a conventional linguistic approach that can be applied reliably due to the occurrence of ambiguous words and ambiguous sentences structures. It needs an a priori conceptual hierarchy database to be constructed.

In contrast, some hybrid approaches are proposed by the researchers. Rajaraman et al. (2002) proposed a concept frame representation which focuses on searching for Noun-Verb-Noun structures in sentences based on syntactic relations. It applies
WordNet for generalization of terms through sense disambiguation. Clariana, et al. (2004) present an approach which relies on a predefined list of domain specific concepts provided by an expert. It considers two concepts to be related if they occur in the same sentence, but does not suggest possible linking phrases. A Two-Phase Concept Map Construction (TP-CMC) algorithm is proposed by Sue et al (2004) to automatically construct a concept map of a course by historical testing records. They apply fuzzy set theory to transform the numeric testing records of learners into symbolic, apply education theory to further refine it, and apply data mining approach to find its grade fuzzy association rules. Then, they use multiple rule types to further analyze the mined rules and a heuristic algorithm is proposed to automatically construct the concept map according to the results of the analysis.

Figure 2.27: A screenshot of Text Analyst (Megaputer Intelligence, 2008)
2.5.4.2 Inference of a concept map

In order to support the automatic inference of concept map, spreading activation (SA) is adopted. Similar to concept maps, the SA model also has its roots in its relationship with human memory (Rumelhart and Norman, 1983). It has often been associated with semantic networks. During spreading, the activation inputs and outputs of nodes in the network are calculated. The output value of the node is fired to all nodes connected to it. Hence, the activation spreads pulse after pulse until a termination condition has been met. The most salient fault of pure SA is that the activation tends to quickly spread over the entire network (Preece, 1981). This shortcoming can be partially overcome by the implementation of rules to control the activation. This new model is called Constrained Spreading Activation (CSA). Some common constraints are the distance constraint, fan-out constraint, path constraint and the activation constraint (Crestani and Lee, 2000).

Concept mapping has been widely accepted to be effective as a learning tool (e.g. Boxtel et al, 1997) and communication tools for sharing ideas (Okebukola, 1992) in OL applications. However, workers create concept maps manually in most of the current applications in OL. The automatic concept map construction techniques are useful to save the time for creating concept maps and the inferences of concept maps may be applied to problem-solving and decision support (Wang et al., 2008b). The representation of narrative data in terms of concept maps has also received little concern.

2.6 Summary

In this chapter, the state of the art of KM and OL is reviewed and discussed. OL
is complementary to KM (Firestone and McElroy, 2004). It is defined as the process of change in individuals and shared thought and action, which is affected by and embedded in the institutions of the organization (Vera and Crossan, 2003). In organizational knowledge, narrative knowledge has the highest potential for leveraging individual and organizational learning (Lämsä and Sintonen, 2006).

The knowledge processes, the facilitating factors for achieving OL, and the current approaches and technologies for achieving OL are discussed. The review shows that most of the existing approaches do not fulfill the requirements needed for the knowledge processes and facilitating factors. In particular, the facilitating factors ‘promoting experimentation, implementing new ideas and tolerating mistakes’, ‘shared vision among individuals and organization’, and ‘encouraging and supporting individual learning’ have received little attention. Moreover, some other limitations including ‘separating learning from working’, ‘labor-intensive, timely and costly methods in narrative knowledge acquisition, sharing, and reuse’, and ‘applying past experience for solving new problems directly and lack of proactive manner for dealing with future situation’ are found in the existing approaches.

During the review of supporting technologies for OL, automatic narrative generation, AI, data mining, and concept mapping are discussed. Most of the previous research work in automatic narrative generation consists of predefined conditions, predefined goals, and inferred post-conditions. The resulting narratives are hence rigid and lack diversification. Moreover, the top-to-bottom approach requires a large amount of work for constructing and maintaining the predefined elements.
It is interesting to note that Case-based Reasoning (CBR) and fuzzy logic has been widely used for supporting OL in the literature. CBR is a suitable technology for storing and retrieving knowledge for future reuse. However, it should be incorporated with other technologies to increase its problem-solving ability. Fuzzy logic is eminently suited to the problems that are found in organizations, but the applications of fuzzy logic in narrative simulation have received relatively little attention. Artificial Neural Network (ANN) is a black box approach in which the cause and effect relationships of inputs and outputs are implicit. As a result it is not suitable to be applied in organizational problems which require evidence-based reasoning. GA is also not relevant in the present study since it is mostly applied in well-defined optimization problems. However, the management of narrative knowledge is always considered as an ill-defined problem. Text mining and concept mapping are useful for converting unstructured narrative text into a structural format that is easy for computation. However, improvement and adaptation are required and this needs to be addressed in this research.

On the whole, the results of the literature review reveal that there is a need for the establishment of a methodology which enables knowledge creation, storage and retrieval, transfer and sharing, and application, as well as fulfilling the facilitating factors, in order to achieve OL. The methodology needs to incorporate the KBS and AI technologies for providing knowledge storage, knowledge sharing and decision support functions for workers’ daily operations. A bottom-up approach for the collection of narratives is much needed for saving time and reducing the cost for maintaining the knowledge updating process.
Knowledge repositories and narrative database are adopted for storing the narrative knowledge. Text mining and concept mapping are required for converting such knowledge into a structural format. Automatic narrative generation and AI technologies are incorporated to generate narrative simulation automatically, so that workers can learn and examine new ideas in simulation in a cost effective, time effective and labour effective manner. The narrative generation requires that scenarios based on multiple narrative resources be constructed, in order to prevent simple and direct usage of previous narratives. Using the methodology, the facilitating factors of OL and the integration of knowledge processes into workers’ daily workflow can be achieved.
An overview of research methodology is provided at the beginning of this chapter. The differences in approach between the traditional and the computational narrative simulation (CNS) are discussed. Hence, the architecture of the computational narrative simulation system (CNSS) is described. CNSS consists of a knowledge-based system (KBS) and a narrative simulation construction system (NSCS) for supporting four knowledge processes which are knowledge creation, knowledge storage and retrieval, knowledge transfer and sharing and knowledge application. The KBS and NSCS are supported by a knowledge repository (KR) and four major algorithms which are fuzzy associated concept mapping (FACM), hybrid case-based reasoning (HCBR), self-associated concept mapping (SACM) and narrative prediction and construction. The benefits of the CNSS are highlighted at the end of this chapter.

### 3.1 Research methodology

The research methodology is shown in Figure 3.1. A literature review is firstly conducted which focuses on organizational learning, computational and narrative simulation, natural language processing, and computational intelligence, etc. Hence, a CNSS is designed which specifies the role, operation, and integration of modules, information flow, and knowledge flow. Then, a prototype of the system is built. The algorithms of the system are evaluated in order to ensure the correct performance of each algorithm developed for the CNSS. The evaluations are carried out by
comparing them with different well known reasoning methodologies by using various public databases. Afterward, a trial implementation is carried out in a selected reference site to apply the whole system. The results of the trial implementation are evaluated through a case study and a controlled experiment.

![Research methodology diagram]

**Figure 3.1: Research methodology**

### 3.2 A comparison between traditional approach and computational narrative simulation (CNS) approach for OL

As shown in Figure 3.2(a), traditional narrative simulation is static and starts from defining the topic of simulation. Based on the selected topics, stories are collected through interviews, observations, etc. It is arguable whether any plausible story, or an actual story should be used. Some research work suggests that it would be more powerful to use an actual contemporary story to support reflection and change (Bliss and Mazur, 1996; Philip, 1994). While some other researchers suggest
that verisimilitude or plausibility is sufficient in narrative (Bruner, 1990; Phillips, 1994).

![Diagram of computational narrative simulation process]

Figure 3.2: A comparison between (a) traditional approach and (b) computational narrative simulation approach

The next step is to develop the story or stories into a narrative simulation exercise. It requires a transformation of a retrospective perspective into an unfolding and interactive format. The story should be condensed and critical decision points or dilemmas are determined. Each decision point or dilemma needs to develop corresponding questions and a choice of answers. At the same time, the users’ characteristics should be considered so that the designed choices are informative and meaningful to the users. Evaluation of the simulation is required after the trial run.
The usability of the system, the relevance of the content, and the abilities for generating meaningful learning and discussion should be evaluated. Finally, the narrative simulation can be used by the targeted users.

The CNS adopts a knowledge management perspective and an intelligent and automatic process which enhances the OL capability of the company and facilitates the generation of narrative simulation. As shown in Figure 3.2(b), CNS works with a workflow system in which the narrative information of knowledge workers’ daily work is retained in its knowledge repository. It starts with the continuous data collection from knowledge workers’ input. The narrative data is digested and converted into a structured format that can be more easily processed by computers. Users can construct a narrative simulation at anytime in the CNS.

The topic of narrative simulation is automatically suggested and the suggested topic would be one which could possibly happen in the near future. The CNS is intended to provide changes to the users instead of just reacting to the users. Based on the topic, the relevant concepts are extracted to form a list of story segments. The story segments are automatically inferred to generate the decision points or learning points which provide the corresponding questions and answer choices. The resulted narrative is then reviewed and revised by the simulation designer. The knowledge of how the revision be performed is retained and accumulated into the knowledge repository for improving the narrative simulation construction for future reuse.

Table 3.1 summarizes the differences between the traditional static narrative simulation and the CNS. The major purpose of traditional narrative simulation is
used for passive learning. Most of the previous research work appears to consist of predefined conditions, predefined goals, and inferred post-conditions. The resulted narratives are hence rigid and lack diversification. The top-to-bottom approach involves a heavy workload for constructing and maintaining the predefined elements. The CNS is a bottom-up and semi-automatic approach for the collection of narratives, which helps to save time and reduces the cost for maintaining the knowledge update. It integrates the knowledge processes which include knowledge acquisition, knowledge sharing, knowledge diffusion and knowledge application and reuse, into the existing workflow.

Table 3.1: Differences between traditional narrative simulation and the CNS

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Traditional narrative simulation</th>
<th>CNS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge management</td>
<td>Designed for passive learning</td>
<td>Designed for reflective and proactive learning</td>
</tr>
<tr>
<td></td>
<td></td>
<td>and integrating knowledge management activities into existing the workflow</td>
</tr>
<tr>
<td>Narrative content selection</td>
<td>Based on the experience of simulation design</td>
<td>Based on the analysis of the computational model</td>
</tr>
<tr>
<td>Data collection</td>
<td>Collected from interviews manually</td>
<td>Collected from existing databases automatically</td>
</tr>
<tr>
<td>Construction method</td>
<td>Adapted from stories manually</td>
<td>Aggregated from stories’ segment automatically</td>
</tr>
<tr>
<td>Knowledge to be shared</td>
<td>Static knowledge, easy to fadeout or outdated</td>
<td>Able to apply to both static and dynamic knowledge</td>
</tr>
<tr>
<td>Maintenance method</td>
<td>No</td>
<td>Automatic update</td>
</tr>
<tr>
<td>Length of time for the</td>
<td>Long</td>
<td>Short</td>
</tr>
<tr>
<td>construction process</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Knowledge of narrative data</td>
<td>Always single story is used</td>
<td>Numerous stories are contributed and reused</td>
</tr>
<tr>
<td>Narrative structure</td>
<td>Single linear narrative</td>
<td>Multi-linear narrative</td>
</tr>
<tr>
<td>Requirement of simulation</td>
<td>Highly experienced people are</td>
<td>Less experienced people can be used</td>
</tr>
<tr>
<td>designer</td>
<td>required</td>
<td></td>
</tr>
<tr>
<td>Quality of narrative</td>
<td>Largely depended on simulation</td>
<td>Less dependence on simulation designer</td>
</tr>
<tr>
<td>simulation</td>
<td>designer</td>
<td></td>
</tr>
</tbody>
</table>
Chapter 3 Computational Narrative Simulation (CNS)

The content of traditional narrative simulation is designed based on the manually collection of narratives by the simulation designer, in which most of the narratives are easily outdated. For the content of CNS, the narrative data is collected continuously during the daily operation of the knowledge workers. Most updated knowledge can be reused for the narrative construction so as to prevent the constructed narrative becoming outdated. At the same time, the cost for maintaining the narrative can be reduced. This also minimizes the effort of the simulation designer and achieves knowledge acquisition of the company.

CNS is able to construct scenarios that would probably occur in the near future. This provides extra time for the knowledge workers to study and analyze the problem before the problem really occurs. Moreover, this helps workers to explore new problem solving methods so as to increase the quality of the solution. The time of narrative construction is significantly reduced by the automatic construction method in the CNS.

Compared to traditional narrative simulation, a multi-linear narrative structure is adopted in the CNS. Figure 3.3 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, so that the plot of the story can be changed based on different decisions made by the narrative simulation users. This provides more information than just using a single story. The knowledge of narrative simulation construction is stored into the knowledge repository for future reuse and most of the work is undertaken by the system in CNS. Hence, a less experienced simulation designer can be used. The quality of traditional narrative simulation is
largely relied on the simulation designer. In the CNS, the quality of the narratives can be assured and maintained more easily.

![Diagram of traditional and multi-linear narrative structures](image)

Figure 3.3: (a) Traditional narrative structure and (b) multi-linear narrative structure

A multi-linear narrative structure is adopted in the CNS. Traditionally, writers construct stories such that a specific audience may experience their story in a single fixed linear form. Books have a linear structure to their text, and thereby inspire a linear approach to writing new content. When computers are added to the writing process, the linear structure of narrative is significantly altered. From Vannevar Bush's proposed Memex system in the 1940's (Bush, 1945), to interactive videodisc projects in the 1970's and 1980's (Perlmutter, 1983), to digital video stories delivered over the internet, computational power has reshaped the traditional linear narrative model and delivers narratives with increasing flexibility and diversity.
In more simplified and commercial manner, multi-linear narrative also has its influence in the classic Choose Your Own Adventure books originated by Packard in the 1970s (Packard, 1979). These books contain a finite number of plot lines and narrative paths, broken up by waypoints at critical moments in the story. At these moments, the reader is prompted to play the role of the characters and make a choice between several possible actions, directing him to another page.

The term multi-linear narrative is used to define a form of multiple linear narratives taken from a highly structured collection of small narrative pieces. These narrative pieces on their own do not constitute a single narrative path or plotline. Instead, they act as building blocks for constructing many different narratives. This type of story defines a form which transcends the linear, in the sense that it is a form from which many linear stories can be made. In the past, many terms have been used by writers and narrative researchers to describe stories which are different from a strict singular path. Massachusetts Institute of Technology (MIT) research scientist and Murray (1997) defines multiform story as “... a written or dramatic narrative that presents a single situation or plotline in multiple versions, versions that would be mutually exclusive in our ordinary experience.” Indeed, this definition goes far to define a narrative form which in essence is linear, yet has many different instances of its linearity.

3.3 Architecture of the computational narrative simulation system (CNSS)

To realize the concept of the CNS approach, a Computational Narrative Simulation System (CNSS) is designed and built. The CNSS includes the following objectives:
(i) To demonstrate the applicability of the CNS approach in current studies as a proof of its concept

(ii) To develop a platform for acquisition, sharing, and replenishment of narrative knowledge

(iii) To develop a set of software components to support the automatic construction of narrative simulation

The architecture of the CNSS is shown in Figure 3.4. There are 2 major applications, which are knowledge-based system (KBS) and narrative simulation construction system (NSCS), for supporting the four knowledge processes which are knowledge creation, storage and retrieval, transfer and sharing, and application, respectively. The KBS is used to realize knowledge storage and retrieval, transfer and sharing, and application, while the NSCS is used to realize knowledge creation, transfer and sharing. The KBS and NSCS are supported by a knowledge repository and four computational intelligent algorithms including fuzzy associated concept mapping (FACM), hybrid case-based reasoning (HCBR), self-associated concept mapping (SACM) and a narrative prediction and construction algorithm. The sources code of the algorithms is available in Appendix I.

3.3.1 Knowledge-based system (KBS)

A schematic diagram of the KBS in the CNSS is depicted in Figure 3.5. The knowledge cycle 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 3.6 depicts the structured and unstructured parts of a case.

Figure 3.4: A framework of the computational narrative simulation system (CNSS)

Figure 3.5: A schematic diagram of the KBS in the CNSS
The structured parts of a case are analyzed by the hybrid case-based reasoning (HCBR) algorithm. Similar cases and recommendations are deduced by the HCBR for workers’ references. They are then revised and stored into the knowledge repository. With the unstructured parts, fuzzy associated concept mapping (FACM) is purposely built for converting the unstructured narratives into structured concept maps as shown in Figure 3.7. Workers can review the automatically generated concept maps and the maps generated by other workers through the system. The revised map is then retained into the knowledge repository for future use. Hence, knowledge sharing, application, and storage are achieved in the KBS. The details of FACM and HCBR are discussed in Sections 3.5 and 3.7 respectively.

![Structured and Unstructured Parts of a Case](image)

**Figure 3.6:** The structured and unstructured parts of a case

### 3.3.2 Narrative simulation construction system (NSCS)

For achieving the knowledge creation and sharing processes in an efficient manner, a NSCS is developed to create narrative simulation automatically. A schematic diagram of the NSCS is shown in Figure 3.8. At any time, the organization can generate narratives based on the input data that is stored into the
knowledge repository during the workers’ daily operations. The simulation designer inputs the criteria of data selection of the simulation. For example, a designer may want to use narrative data which were created within a certain period of time, so that outdated narratives are negated in the creation of narrative simulation.

Figure 3.7: Conversion of an unstructured narrative into a structured concept map

Based on the designer’s specifications, a narrative prediction and construction algorithm generates a narrative segment which is the beginning of the whole narrative simulation (see Figure 3.9). Based on the concepts of the initial narrative, Hybrid Case-based Reasoning (HCBR) is then used to infer the decision choices. Self associated concept map (SACM) is then applied to associate the relevant concepts related to each decision choice. The associated concepts are consolidated to formulate an intermediate narrative, and then the termination of narrative is determined. If it is not the end of the narrative, the HCBR is applied again for the inference of decision choices for the remaining intermediate narratives. The whole
process continues looping again and again until all decision choices terminate. As shown in Figure 3.10, a designer makes use of a narrative construction toolkit to review and revise the narrative simulation. A web interface is then generated for learners to use.

Figure 3.8: A schematic diagram of the NSCS in the CNSS

Figure 3.9: A schematic diagram of construction of a multi-linear narrative
3.3.3 Knowledge repository

Both the KBS and the NSCS rely on the knowledge repository for knowledge storage and retrieval. The knowledge repository of the CNSS consists of a case library and databases for storing the information related to the customer, the staff,
the customer privileges, business information, reasoning list, the thesaurus model of the business and the narrative construction data and rules. These data are continually updated and shared by all other modules. The case library is made up of previous working cases of the organization. Cases in the case library are made up of three parts namely the case number, case indexes and the solution sets. Structure of each case can be represented as:

\[ \text{Case}(\text{case\_number}, \text{case\_indexes}, \text{contents}, \text{solutions}) \]

A case number is assigned by the system sequentially to each case to provide with a unique designation. The case indexes are the identities of the cases that are entered into the case library so as to ensure that they can be retrieved efficiently and effectively. The contents include extra information of the cases for workers reference. As different customers may have different privileges for receiving services, the recommendations may vary for different customers. The solution sets contains the decision making results and recommendations of services of the cases.

A thesaurus model in the knowledge repository stores the concepts and interrelationships among concepts. The thesaurus is used for promoting consistency in indexing and retrieval of concepts. It is built from the bottom up approach which starts with merging the existing thesauri into one. In the present study, the development of a thesaurus is referenced to WordNet (Fellbaum, 1998). It is useful for generalization of terms through sense disambiguation so any such domain dependent databases do not need to be constructed.
3.3.4 Computational intelligent algorithms

A series of computational intelligent algorithms have been purposely developed for supporting CNSS which include fuzzy associated concept mapping (FACM), hybrid case-based reasoning (HCBR), self-associated concept mapping (SACM), and narrative prediction and construction. They are purposely built by the author to address the limitations and deficiencies of the existing theories as discussed in Chapter 2.

FACM uses the syntactic structure of the sentences to find relations between the words. The relations and concepts are generated from the natural language text itself rather than retrieved from predefined ontologies. Hence, it enables the approach to be applied in any domains without initial knowledge capture. It also ensures that the intentions of the text author can be preserved by using the words generated from the document itself. An anaphoric resolution is applied based on rule-based reasoning (RBR) and case-based reasoning (CBR) for solving ambiguities arising during the syntactic analysis. This enables a dynamic method of anaphoric resolution that is continually improved. Furthermore, FACM produces concepts and relationships based on multi-word text structures rather than on individual words, making the concept and relationship labels more complete.

The existing narrative generation methods consist of predefined conditions, predefined goals, and inferred post-conditions. The resulting narratives are hence rigid and suffer from a lack of diversification. In contrast to the methods, the narrative prediction and construction algorithm combines multiple narratives into a
single narrative in order to prevent simple and direct usage of past narratives. The algorithm clusters propositions in the past narratives and predicts propositions that would probably happen in the near future. The predicted propositions are then filtered and grouped to form a new narrative.

HCBR is developed based on a parallel flow of CBR and RBR. It makes fully use of both knowledge bases and compensates the disadvantages of CBR and RBR. The work differs from the past studies in which it combines the results of CBR and RBR by adopting fuzzy set theory. In contrast to the traditional methodologies which provide rather simple suggestions at a specific point in time, the HCBR is capable of providing suggestions at any stages in the workflow.

SACM extends the use of concept mapping by developing the idea of self-construction and automatic problem solving to traditional concept maps. SACM can be automatically constructed and dynamically updated from a knowledge repository with structured historical records. A Constrained Fuzzy Spreading Activation (CFSA) model is incorporated in the SACM which enables the decision supporting function for providing more precise, rapid and automatic decisions.

These algorithms are the core part of this research which possess certain degree of originality and have made significant contribution to the advancement of the technology in narrative simulation. They provide an important means for achieving the computational narrative simulation. The theory and working principles for the
each algorithm are discussed in the Sections 3.5 to 3.8 while the performances of them are evaluated in Chapter 4.

3.4 Assumptions of the CNS methodology for OL

In the development of the CNS and hence CNSS, the following assumptions are realized:

(i) Successful organizational learning (OL) requires the management and workers’ buy-in, organizational atmosphere of promoting experimentation, and believes on implementing new idea, tolerating mistakes, sharing and encouraging learning. Without these factors, the system will not work properly. As a result, it is assume that the organizational learning environment is ready for the implementation of the CNS methodology.

(ii) The implementation of the CNS method requires a workflow system for acquiring knowledge from the knowledge workers. Since the workflow system provides an efficient and effective way to incorporate the daily operations of work and knowledge management processes together for organizations, it is becoming necessary for organizations to fulfill the basic requirements of their work as well as to achieve different knowledge management activities. Although it needs extra time for constructing the workflow system, the benefit obtained and the time reduced in narrative simulation make it worth while to do so.

(iii) Instead of collecting the best practices, the CNS approach dedicates on gathering and synthesizing current practices of the organization which aims at acquiring the shared working practice, and facilitating and stimulating learning. As a result, the quality of the narrative simulations depends largely
on the daily input of the knowledge workers. This shifts the effort and loading from the individual knowledge of narrative simulation designer into collective wisdom. However, the narrative simulations may only be used to certain group of people (i.e. within the industry or within the organization). Furthermore, the lexical choice may be limited due to the collected narratives.

(iv) In order to construct the multi-linear narrative automatically, the collected narratives must consist of at least three narrative segments which are the beginning segment, the segment(s) for decision(s), and the segment(s) for consequence(s). The beginning segment describes the background of the narrative, while the segment for decision represents the action taken based on the beginning segment. The segment for consequence indicates the results occurred after taking the corresponding action. The three parts must be clearly identified and recorded in order to implement the CNS.

3.5 Fuzzy associated concept mapping (FACM)

As mentioned in the KBS in Section 3.3.1, FACM has been developed for the conversion of unstructured narrative data into structured concepts maps which are easy for the computer to process. As shown in Figure 3.11, FACM consists of an automatic process and an interactive process. The unstructured text is first preprocessed by an ad hoc sentence boundary detection algorithm based on regular expressions such as the new line character, full stop, and question mark. Each individual sentence is then parsed, based on an augmented grammar for syntactic analysis. This step simultaneously tags each word with its part-of-speech (POS) using an in-house developed POS tagger and produces a parse tree for the sentence.
Chapter 3 Computational Narrative Simulation (CNS)

The POS tagger is adopted from WordNet (Fellbaum, 1998). The notation of the tagset is shown in Appendix A. A detailed description of the tagset is available in Satorini (1990). During the parsing stage, interjections, list item markers, and short sentences are filtered out.

3.5.1 Anaphoric resolution

Based on Novak & Cañas (2006), a concept map is composed of propositions. A proposition in a concept map is defined as a statement about some objects or events in the universe, either naturally occurring or constructed. Generally, the subject of a sentence represents a concept. The object of a sentence, which is in the verbal phrase, represents a second concept. The relationship between two concepts is identified by the main verb in a sentence. The POS tagger identifies simple noun phrases.

In order to extract more complex terms and solve the ambiguities arising from this process, anaphoric resolution is used, based on rule based reasoning (RBR) and case based reasoning (CBR). In RBR, syntactic rules are applied for extracting the noun phrases and verb phrases. The rules used in the present study are shown in Appendix B. Two examples of the rules are given as follows:

np: <det><jj>*<np>++<in><vbg><jj>*<np>*

vp: <rb><vp>+<in><rb>*<vp>*

where <det> is a determiner, <jj> is an adjective, <np> is a noun phrase, <in> is a preposition, <vbg> is a verb gerund, <rb> is an adverb, <vp> is a verb phrase, * is an operator that means zero or n occurrences of an item, and + is an operator that means at least one occurrence.
Since there are numerous different writing styles, RBR is not able to solve all the cases. If RBR is not able to solve the problem, it will pass the problem to the CBR module. In the present study, each case sent to the CBR consists of a problem, a problem context and a solution that was used to solve the problem. The problem is the ambiguous sentence and the problem context is the previous sentence of the ambiguous sentence. Each word of both sentences is tagged with its POS. The solution is the amended sentence(s) with the tagged POS of the ambiguous sentence. When the previous sentence is also an ambiguous sentence, it is necessary to solve the previous sentence first. By using the amended previous sentence as the problem context, the ambiguous sentence can then be resolved. When there is a new ambiguous sentence, the model extracts the syntactic and POS classification in the
two sentences (the ambiguous one and its previous one) as a new case. Then, it
searches for a similar case in the case base that was resolved in the past. The solution
of the most similar case is adapted to this new situation by finding the word that has
the same syntactic function.

The similarity between the new case and old cases is calculated based on the
nearest neighbour matching (Aamodt & Plaza, 1994). The similarity is determined as
follows:

\[
\text{Similarity} = \frac{\sum_{j=1}^{m} w_j \times \text{sim}(v_j^o, v_j^f)}{\sum_{j=1}^{m} w_j} \tag{3.1}
\]

where \( m \) is the number of inputs, \( w_j \) is the weighting of the \( j \)th POS, \( v_j^o \) and
\( v_j^f \) are types of the \( j \)th POS of the input case and that of the retrieved cases,
\( \text{sim}(v_j^o, v_j^f) \) is the similarity function for the \( j \)th POS as follows:

\[
\text{sim}(v_j^o, v_j^f) = \begin{cases} 
1 & \text{if } v_j^o = v_j^f \\
0 & \text{if } v_j^o \neq v_j^f
\end{cases} \tag{3.2}
\]

An example about the conjunction problem is depicted in Figure 3.12, in which
\(<\text{vp}>\) is verb phrase, \(<\text{np}>\) is noun phrase, and \(<\text{cc}>\) is conjunction. The case is
encoded into the case base according to the format as shown in Figure 3.13. The
problem set is encoded by storing the POS of the sentence, and the solution set is
encoded by storing the corresponding positions of the POS. These are separated by
commas and semicolons to form the concept-link-concept propositions.
Chapter 3 Computational Narrative Simulation (CNS)

The ability of anaphora resolution improves with the increasing size of the case base. After many texts have been analyzed, a considerable case base is available. It is possible to have a dynamic method for anaphoric resolution that is continually improved as it is used. In the present study, the case base consists of 21 cases which are shown in Appendix C. Adopting the anaphoric resolution not only helps to deal with the ambiguity, but also converts the input sentences into a concept-link-concept format (e.g. a noun phrase - verb phrase - noun phrase format).

Traditional methods utilize simple rules to solve the anaphoric resolution problem. They use a large number of rules which makes it difficult to resolve the conflicts among rules. Also, these rules cannot be learnt adaptively. For example, CogNiac (Baldwin, 1997) is a rule-based approach to anaphoric resolution based on a set of high confidence rules which are successively applied to the pronoun under consideration. The rules are ordered according to their importance and their relevance to anaphoric resolution. The processing of pronoun stops when one rule is satisfied.
Some other anaphoric tools can be found in Kennedy and Boguraev (1996), Lappin and Leass (1994), Mitkov (1998), etc. By integrating CBR and RBR anaphoric resolution, a smaller number of rules are used (16 rules are used in this research) and the self-learning capability can be achieved by continuously updating case base.

3.5.2 Word normalization

After anaphoric resolution, the extracted concepts undergo a word normalization process. Natural language contains variations of words that refer to the same entity, and may use multiple synonyms. Different linguistic operations can occur within the noun phrases. These operations either modify the structure or the length of an existing term. In the present study, WordNet (Fellbaum, 1998) is used to determine synonymic relations to deal with number variants and semantic variants. Moreover, simple rules are used to deal with spelling variants and syntactic variants. The shortest terms among the variants are extracted as the concept labels since concept labels in concept maps are usually short in length. Examples of the variants are shown in Table 3.2.

<table>
<thead>
<tr>
<th>Variation Type</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number</td>
<td>“techniques” and “technique”</td>
</tr>
<tr>
<td>Semantic</td>
<td>“classification” and “categorization”</td>
</tr>
<tr>
<td>Spelling</td>
<td>“cluster-based” and “cluster based”</td>
</tr>
<tr>
<td>Syntactic</td>
<td>“information retrieval” and “retrieval of information”</td>
</tr>
</tbody>
</table>

3.5.3 Graphical representation

Since concepts are represented in a hierarchical fashion with the most inclusive,
most general concepts at the top of the map and the more specific, less general concepts arranged hierarchically below, a term weighting method is used for ranking the importance of the concepts. Several term weighting methods (Salton and Buckley, 1988; Hulth, 2003) have been used for calculating term importance. Most of them rely on the relative importance of terms across a collection of documents. Since the aim of the present study is to develop methods to process the source document independently from other incoming documents, such methods are not suitable. Hence, a simple term frequency in the document is used for calculating term importance, which has achieved some success when additional context information is unavailable (Salton and Buckley, 1988). In the final step, the concept phrases and linking phrases are gathered to construct the concept map. An auto-layout function is used for producing an initial graphical representation of the concept map.

3.5.4 Proposition recommendation

The proposition recommendation is used to suggest propositions that are not found obviously among the sentences. It is an interactive process that facilitates user learning. It adopts term weighting and heuristic fuzzy rules. The term weighting method is combined with heuristic fuzzy rules for suggesting the linkage between high occurrences of pairs of concept phrases. Two examples of fuzzy rules are shown as follows:

IF the frequency of two concepts co-existing in the same sentence is High, THEN the relationship is High

IF the frequency of two concepts co-existing in the neighbor sentence is High, THEN the relationship is Medium
The normalized frequency of concept $i$ and concept $j$ co-existing in the same or adjacent sentence is calculated by Equation (3.4):

$$F_{ij} = \frac{N_{ij}}{N_{\text{max}}}$$  \hspace{1cm} (3.4)\

where $F_{ij}$ is the normalized frequency of concept $i$ and concept $j$ co-existing in the same or adjacent sentence, $N_{ij}$ is the number of count of concept $i$ and concept $j$ co-existing in the same or adjacent sentence, $N_{\text{max}}$ is the maximum number of count among all concepts co-existing in the same or adjacent sentence.

The fuzzy values of the normalized frequencies are determined according to the corresponding membership function. As shown in Figure 3.14, a simple membership function of the fuzzy values of the normalized frequency is adopted in the present study. The corresponding degree(s) of the normalized frequency is/are assigned to be the corresponding degree(s) of membership. For example, if $F_{ij} = 0.6$, then the fuzzy value is (0.7 High; 0.2 Medium) and the fuzzy rules which contains “Frequency: High” and “Frequency: Medium” are fired. Then, the clipped membership functions are aggregated into a single fuzzy set and defuzzified by the centre of gravity (COG) method (Hirota et. al., 1998). The membership function of the relationship between concepts is shown in Figure 3.15. The COG of fuzzy set $A$ on the interval $a_1$ to $a_2$ with membership function $\mu_A$ is given by Equation 3.5:

$$CG(A) = \frac{\int_{a_1}^{a_2} x\mu_A(x)dx}{\int_{a_1}^{a_2} \mu_A(x)dx}$$  \hspace{1cm} (3.5)
For example, the consequent membership function of the relationship between the concepts is (0.7 High, 0.2 Medium). Based on the membership function of the relationship between concepts as shown in Figure 3.15, the consequent membership functions are clipped (see Figure 3.16). Based on the COG method, $CG(A) = 0.57$. Finally, a list of suggested concept pairs is ordered by descending weighting of the relationships, $CG(A)$. The concept map is then revised by the user and is stored in the knowledge repository.

![Figure 3.14: The membership function of the normalized frequency](image1)

![Figure 3.15: The membership function of the relationship between concepts](image2)
3.6 Narrative prediction and construction

After the conversion process of narrative to concept map, propositions are collected. In the NSCS, propositions are grouped according to time index such as the entry time of the narrative. As a result, a computational forecasting method is used for the prediction of the expected number of count of each proposition and the expected sum of propositions of the requested narrative. In the present study, an adaptive time-series model (Cheung et al., 1995, Lee et. al, 1997), which makes use of an autoregressive (AR) time-series model is used to predict the propositions.

Figure 3.17 shows a schematic diagram of the adaptive time-series modeling method. For a \( n \) th order autoregressive (AR) time-series, the predicted data value \( \hat{S}_j(k) \) is the expected number of counts of proposition \( j \) (or the expected sum of propositions of the predicted narrative), which is expressed as a linear combination of the \( n \) previous values, i.e.:

\[
\hat{S}_j(k) = \sum_{i=1}^{n} a_i(k)S_j(k - i) \tag{3.6}
\]

where \( S_j(k) \) is sampled data of the number of counts of proposition \( j \) (or the

Figure 3.16: The clipped membership function of the relationship between concepts
averaged sum of propositions of narratives) at time index $k$, and $a_i(k)$ are the time-series coefficients.

![Diagram of adaptive time-series modeling method](image)

Figure 3.17: A schematic diagram of the adaptive time-series modeling method

(adapted from Lee et. al, 1997)

A $n$ th order time-series coefficient vector is defined as:

$$a(k) = [a_1(k), a_2(k), \ldots, a_n(k)]^T$$  \hspace{1cm} (3.7)

A vector of current and $n-1$ past data is defined as:

$$S^T(k) = [S(k)S(k-1)\ldots S(k-n)]$$ \hspace{1cm} (3.8)

From Equations (3.6), (3.7) and (3.8), Equation (3.6) can be rewritten as:

$$\hat{S}_j(k) = a^T(k)S_j(k-1)$$ \hspace{1cm} (3.9)

The prediction error $e(k)$ is defined as the difference between the sampled data $S(k)$ and the AR model predicted value $\hat{S}(k)$, i.e.,
If the error is greater than the prerequisite tolerance, the prediction process stops and the model will be re-calibrated or fine-tuned. Otherwise, the process proceeds to update the coefficients of the AR time-series for the next prediction cycle. Based on the prediction error, the AR time-series coefficients can be modified to adapt to the change in the sampled data. This is accomplished by using an Enhanced Least Mean Square (ELMS) adaptive filter algorithm developed by (Cheung et al., 1995, Lee et al., 1997). The attractive feature of the ELMS algorithm lies in its relative simplicity which demands for less computational resources.

The ELMS algorithm starts with the update of the filter coefficient vector $a(k+1)$ by incrementing the old estimate of the vector $a(k)$ by an amount proportional to the product of the input vector $S^T(k)$ and error signal $e(k)$. The filter coefficients are adjusted every time a new data point is sampled. Each adjustment is an effort to minimize the squared error signal at that instant, $e^2(k)$. In the ELMS algorithm, the modification of the AR model coefficient vector $a$ is achieved by Equations (3.11) and (3.12):

$$a(k+1) = a(k) + \beta e(k)y(k)$$  \hspace{1cm} (3.11)

and

$$e(k) = y(k) - y^T(k-1)a(k)$$  \hspace{1cm} (3.12)

where $\beta$ is the adaptation gain which determines the step size of change of $a$ at each adjustment; $y(k)$ is the measurement vector at $k$-th instance of time which

$$e(k) = S(k) - \hat{S}(k)$$  \hspace{1cm} (3.10)
contains the current \( n - 1 \) past signal data samples, \( e(k) \) is the prediction error at \( k \)-th instance of time.

For stability and convergence of the ELMS algorithm, the coefficient vector \( a(k) \) of the filter approaches an optimal value \( a_{opt} \) as the number of iterations \( k \) approaches infinity. The ELMS algorithm has two different conditions for convergence which are Convergence in the Mean and Convergence in the Mean Square (Haykin, 1984). For the ELMS algorithm, the optimal values \( a_{opt}(0) \) and \( y_{opt}(0) \) are used. The optimal values \( a_{opt}(0) \) and \( y_{opt}(0) \) are found by an iteration algorithm. The iteration algorithm changes each filter parameter i.e. the order \( n \), the adaptation gain \( \beta \), the values \( a(0) \) and \( y(0) \) one by one inside a predetermined iteration range. The iteration range is bounded by the conditions of convergence and the sum of squared errors (SSE). The set of parameters which gives the minimum value for SSE within the iteration range will be selected as the optimum filter parameters. Although the algorithm may search for the sub-optimal parameters, the performance and stability of the filter can be guaranteed within the iteration ranges.

Based on the predicted sum of propositions for the requested narrative by the concept prediction model, propositions are grouped into proposition groups. The proposition groups are then summed and ranked by the value of the number of counts of each proposition. Then, the groups are checked with the propositions’ conflicts which are stored inside the knowledge repositories. For example, a proposition “Client has schizophrenia” conflicts with the proposition “Client does not have schizophrenia”. The conflicting groups are filtered and the remaining group
with the highest number of counts is selected. The propositions in that group are combined as the resultant narrative.

Figure 3.18: An illustrative example of narrative construction

An illustrative example of narrative construction is shown in Figure 3.18. It is assumed that there are only 3 propositions in the knowledge repository. The expected values for the 3 propositions A, B, and C are 5, 4, and 6, respectively, and the expected sum of propositions is 2. The 3 propositions are then grouped based on the expected sum of propositions, so that each group contains 2 propositions. As a
result, the 3 groups are AB, AC, and BC. Hence, the 3 groups are summed and ranked based on the expected values of the corresponding propositions. It is assumed that proposition A conflicts with proposition C, and proposition B does not conflict with proposition C, and so group BC is selected as the resulting narrative group.

### 3.7 Hybrid case-based reasoning (HCBR)

HCBR supports the decision support process in the KBS. It also provides support for the construction of the decision points, questions and answer choices in the NSCS. HCBR is developed by combining the aspects of case-based reasoning (CBR), rule-based reasoning (RBR) and fuzzy theory. As shown in Figure 3.19, HCBR is composed of three main parts which include CBR, RBR and the combination of CBR and RBR, respectively. The knowledge base of CBR is a case base of the documented experience while that for RBR is a set of IF-THEN rules based on the expert rules embedded for decision support. Fuzzy theory is adopted to deal with the uncertain nature of problem solving.

#### 3.7.1 Case-based reasoning (CBR)

The input problem is decomposed into different features for computation. The CBR consists of a case base that contains past cases of the knowledge work, a similarity measure that calculates the similarity between the input data and the past cases, and an inference engine that deduces the conclusion based on the most similar case. The system performs CBR according to the following steps:

(i) New data are entered.

(ii) Corresponding features that used for similarity analysis are extracted from the new data and previous cases.
(iii) Corresponding weighting set is selected. The weightings are determined by the experts in the knowledge domain.

(iv) The new data are compared with all past cases in the case base. The similarities between the new case and past cases are computed by the similarity function.

(v) The case that obtains the highest similarity is selected and the conclusion is deduced based on the solution of the case.

![Diagram of hybrid case-based reasoning]

Figure 3.19: The schematic diagram of the hybrid case-based reasoning

There are four different types of field values that are used for similarity analysis. They include numerical value (e.g. age: 17), symbolic value (e.g. place of birth: Hong Kong), fuzzy value (e.g. peer relationship: Poor) and multi-symbolic value (e.g.
symptoms: delusion; visual hallucinations). For numerical values, the similarity between a new case and other cases stored in the case base is calculated based on the normalized distance of the features between two cases. For symbolic values, if the values are same, the similarity is 1, otherwise, the similarity is 0. For fuzzy values, the similarity is calculated based on intersectional area of the corresponding fuzzy values. For multi-symbolic values, the jaccard coefficient is applied.

The similarity between $i$-th features of two cases is computed based on the Equations (3.13) to (3.21):

For numerical value, the similarity is calculated based on the normalized distance of the feature between two cases:

$$s_{ij} = 1 - \frac{|v_{i0} - v_{ij}|}{max_i - min_i}$$  \hspace{1cm} (3.13)

For symbolic value:

$$s_{ij} = 1 \text{ if } v_{i0} = v_{ij}$$  \hspace{1cm} (3.14)

$$s_{ij} = 0 \text{ if } v_{i0} \neq v_{ij}$$  \hspace{1cm} (3.15)

where $j = 1..k$, where $j$ is the number of cases in the case base, $i = 1..n$, where $n$ is the number of extracted features from the new case, $v_{i0}$, $v_{ij}$ are the values of the $i$-th feature of the new case and that of the $j$-th case in the case base, respectively, $max_i$ and $min_i$ are the maximum and minimum values of the $i$-th feature, respectively, and $s_{ij}$ is the similarity between the $i$-th feature of the new case and the $j$-th case in the case base.
For fuzzy value, there are several methods for the determination of similarity. Since the fuzzy set used in the present study becomes a single linguistic value, the traditional methods of fuzzy similarity that summarized by Chen et al (1995) cannot deal with this problem. Therefore, a new approach is presented and discussed below.

The degree of similarity of the $i$-th feature for fuzzy value is calculated by the intersectional area of the corresponding fuzzy values:

$$s_{ij} = \frac{Area(v_{i0}) \cap Area(v_{j})}{Area(v_{i0}) \cup Area(v_{j})} = \frac{Area(v_{i0}) \cap Area(v_{j})}{Area(v_{i0}) + Area(v_{j}) - Area(v_{i0}) \cap Area(v_{j})} \quad (3.16)$$

$$Area(A) = \int_{a_1}^{a_2} \mu_A(x)dx \quad (3.17)$$

where $\mu_A$ is the normalized membership function of $A$, $Area(A)$ is the area of $A$, and $a_1$ and $a_2$ are the minimum and maximum boundaries of $Area(A)$, respectively. For the fuzzy values that have two membership functions, the intersection area of these two values is calculated by:

$$Area(A) \cap Area(B) = \int_{a_1}^{a_2} \mu_A(x)dx + \int_{a_1}^{ab} \mu_B(x)dx \quad (3.18)$$

where $ab$ is the intersection point of $Area(A)$ and $Area(B)$ which is shown in Figure 3.20. For multi-symbolic value, the Jaccard coefficient is used:

$$s_{ij} = \frac{|v_{i0} \cap v_{j}|}{c + d - |v_{i0} \cap v_{j}|} \quad (3.19)$$

where $v_{i0}$ and $v_{j}$ are multi-symbolic values, $v_{i0} = (v_{i01}, v_{i02}, \ldots, v_{i0c})$, $v_{j} = (v_{j1}, v_{j2}, \ldots, v_{j0d})$, $v_{i01}, v_{i02}, \ldots, v_{i0c}$, $v_{j1}, v_{j2}, \ldots, v_{j0d}$ are symbolic values, $|v_{i0} \cap v_{j}|$ is the number of elements appearing jointly in $v_{i0}$ and $v_{j}$, and $c$ is the
number of elements in $v_{ij0}$, and $d$ is the number of elements in $v_{ij}$.

The similarity between two cases can be expressed as:

$$S_j = \frac{\sum_{i=1}^{n} w_i s_{ij}}{\sum_{i=1}^{n} w_i}$$  \hspace{1cm} (3.20)$$

$$S_{cb} = \text{Max}(S_j : j = 1...k)$$  \hspace{1cm} (3.21)$$

where $S_j$ is the similarity between the new case and the $j$-th case in the case base, $S_{cb}$ is the highest similarity among $S_j$, and $w_i$ is the weighting of the $i$-th feature.

![Figure 3.20: The similarity of fuzzy sets](image)

The solution is represented in the following format:

Solution of CBR = \{\mathbf{C}_{cb}, \mathbf{I}_{cb}, \mathbf{L}_{cb}\}

where $\mathbf{C}_{cb}$ is a set of conclusions of the case that has the highest similarity in CBR, $\mathbf{C}_{cb} = (C_{cb1}, C_{cb2}, \ldots, C_{cbq})$, $\mathbf{I}_{cb}$ is a set of intensities of the case that has the highest similarity in CBR, $\mathbf{I}_{cb} = (I_{cb1}, I_{cb2}, \ldots, I_{cbq})$, $q$ is the number of
conclusions of the case that has the highest similarity in CBR, \( C_{cbri} \) is a symbolic value and the \( i \)-th conclusion of the case that has the highest similarity in CBR, and \( I_{cbri} \) is a numerical value and the \( i \)-th intensity of the conclusion of the case that has the highest similarity in CBR.

### 3.7.2 Rule-based reasoning (RBR)

The RBR algorithm of the system consists of a rule base and an inference engine. The rule base contains a set of rules for supporting the knowledge work. The rules are obtained from the experts in the business domain. The inference engine is used for deducing the conclusion on the basis of the input and the rules. The system performs RBR according to the following steps:

(i) New data are entered.

(ii) Corresponding features that used for RBR are extracted from the new data.

(iii) The new data and all the rules in the rule base are compared. Rules that matched the conditions of the rules are fired.

(iv) The conclusions of the fired rules are merged by fuzzy set theory.

The general form of the rules is expressed as follows:

\[
\text{IF } \langle \text{Condition} \rangle \text{ THEN } \langle \text{Conclusion} \rangle \text{ WITH } \langle \text{Degree} \rangle \text{ WEIGHT } \langle \text{Confidence} \rangle
\]

Where \( \langle \text{Condition} \rangle \) represents the required values of specified features, \( \langle \text{Conclusion} \rangle \) represents the suggested treatment planning activity, \( \langle \text{Degree} \rangle \) represents the suggested treatment planning intensity, it is a fuzzy value, and \( \langle \text{Confidence} \rangle \) represents the level of confidence of this rule, it is a numerical value in \([0, 1]\).
The solution of RBR is represented in the following format:

\[
\text{Solution of RBR} = \{C_{rhr}, I_{rhr}, L_{rhr}\}
\]

where \( C_{rhr} \) is a set of merged conclusions, \( C_{rhr} = (C_{rhr1}, C_{rhr2}, \ldots, C_{rhrp}) \)

\( I_{rhr} \) is a set of merged intensities, \( I_{rhr} = (I_{rhr1}, I_{rhr2}, \ldots, I_{rhrp}) \)

\( L_{rhr} \) is a set of merged levels of confidence, \( L_{rhr} = (L_{rhr1}, L_{rhr2}, \ldots, L_{rhrp}) \)

It is deduced by the following equations:

\[
C_{rhr} = C_1 \cup C_2 \cup \ldots C_r \tag{3.22}
\]

\[
I_{rhr} = \text{Merge}_I(I_1, I_2, \ldots, I_r) \tag{3.23}
\]

\[
L_{rhr} = \text{Merge}_L(L_1, L_2, \ldots, L_r) \tag{3.24}
\]

where \( r \) is the number of fired rules, \( C_i \) is a symbolic value and the conclusion of the \( i \)-th fired rule, \( I_i \) is a fuzzy value and the intensity of the \( i \)-th fired rule, \( L_i \) is a numerical value and level of confidence of the \( i \)-th fired rule, \( p \) is the number of distinct conclusions of all fired rules, \( C_{rhi} \) is a symbolic value and the \( i \)-th conclusion of \( C_{rhr} \), \( I_{rhi} \) is a fuzzy value and the \( i \)-th intensity of \( I_{rhr} \), and \( L_{rhi} \) is a numerical value and the \( i \)-th level of confidence of \( L_{rhr} \).

For \( C_{rhr} \), only unique conclusions are selected. For example:

\[
C_1 \cup C_2 = (C_i) \text{ if } C_i = C_2
\]

\[
C_1 \cup C_2 = (C_1, C_2) \text{ if } C_1 \neq C_2
\]

\[
C_1 \cup C_2 \cup C_3 = (C_1) \text{ if } C_1 = C_2 = C_3
\]

\[
C_1 \cup C_2 \cup C_3 = (C_1, C_2) \text{ if } C_1 = C_2 \text{ or } C_2 = C_3
\]

\[
C_1 \cup C_2 \cup C_3 = (C_1, C_2, C_3) \text{ if } C_1 \neq C_2 \text{ and } C_i \neq C_j \text{ and } C_2 \neq C_3
\]
For $Merge_i()$, if the conclusion is not unique, the maximum value of intensity among the intensities that have the same conclusion is selected. Otherwise, corresponding values of intensities are selected. For example:

$Merge_i(I_1, I_2) = \text{Max}(I_1, I_2)$ if $C_1 = C_2$

$Merge_i(I_1, I_2) = (I_1, I_2)$ if $C_1 \neq C_2$

$Merge_i(I_1, I_2, I_3) = \text{Max}(I_1, I_2, I_3)$ if $C_1 = C_2 = C_3$

$Merge_i(I_1, I_2, I_3) = (\text{Max}(I_1, I_2), I_3)$ if $C_1 = C_2$ and $C_1 \neq C_3$

$Merge_i(I_1, I_2, I_3) = (I_1, I_2, I_3)$ if $C_1 \neq C_2$ and $C_1 \neq C_3$ and $C_2 \neq C_3$

For $Merge_L()$, corresponding values of the level of confidence are selected based on the result of $Merge_i()$. For example:

$Merge_L(L_1, L_2) = L_1$ if $Merge_i(I_1, I_2) = I_1$

$Merge_L(L_1, L_2) = L_2$ if $Merge_i(I_1, I_2) = I_2$

$Merge_L(L_1, L_2) = (L_1, L_2)$ if $Merge_i(I_1, I_2) = (I_1, I_2)$

3.7.3 Combination of CBR and RBR

The remaining part of the HCBR is the combination of CBR and RBR. The inferred result of CBR and RBR are combined by adopting fuzzy theories. The revised case is retained as a new case in the KR. The description together with the solution of the confirmed case is then stored in the KR for future reuse. The combination of CBR and RBR consists of the following steps:

(i) The solutions of CBR and RBR are combined based on the combination method. It is then sorted according to the combined levels of confidence.

(ii) The solution provided by the system is adjusted by the knowledge workers.
and the detail of adjustment is depended on the knowledge workers themselves. The revised solution is then applied to the real environment.

(iii) After case termination, the actual result generated from the real environment is compared with the solution provided by the system. If a considerable tolerance exists, a series of corrective actions is then taken. They include the modification of the rule base and the fine-tuning of weightings of the CBR and the combination.

(iv) The actual result is then stored into the case base for future reuse.

The solution of combining CBR and RBR is represented in the following format:

Solution of combining CBR and RBR = \( \{ C_{\text{comb}}, I_{\text{comb}}, L_{\text{comb}} \} \). The solutions of CBR and RBR are combined based on the Equations (3.25) to (3.32):

\[
C_{\text{comb}} = C_{\text{ehr}} \cup C_{\text{rbr}}
\]  

(3.25)

For conclusions that exist in both the results of CBR and RBR:

\[
L_{\text{comb}} = \frac{w_{\text{ehr}}\ S_{\text{ehr}} + w_{\text{rbr}}L_{\text{rbr}}}{w_{\text{ehr}} + w_{\text{rbr}}}
\]  

(3.26)

\[
I_{\text{comb}} = \frac{w_{\text{ehr}}\ S_{\text{ehr}}I_{\text{ehr}} + w_{\text{rbr}}L_{\text{rbr}}CG(I_{\text{rbr}})}{w_{\text{ehr}}S_{\text{ehr}} + w_{\text{rbr}}L_{\text{rbr}}}
\]  

(3.27)

For conclusions that exist in the results of CBR only:

\[
L_{\text{comb}} = S_{\text{ehr}}
\]  

(3.28)

\[
I_{\text{comb}} = I_{\text{ehr}}
\]  

(3.29)
For conclusions that exist in the results of RBR only:

\[ L_{\text{comb}} = L_{\text{rbr}} \]  \hspace{1cm} (3.30)

\[ I_{\text{comb}} = CG(L_{\text{rbr}}) \]  \hspace{1cm} (3.31)

The numerical value of the fuzzy value is determined by the center of gravity of \( A \):

\[ CG(A) = \frac{\int_{a_1}^{a_2} x \mu_A(x) \, dx}{\int_{a_1}^{a_2} \mu_A(x) \, dx} \]  \hspace{1cm} (3.32)

where \( C_{\text{comb}} \) is a set of conclusions of combining the solutions of CBR and RBR, \( C_{\text{comb}} = (C_{\text{comb}_1}, C_{\text{comb}_2}, \ldots, C_{\text{comb}_t}) \), \( I_{\text{comb}} \) is a set of intensities of combining the solutions of CBR and RBR, \( I_{\text{comb}} = (I_{\text{comb}_1}, I_{\text{comb}_2}, \ldots, I_{\text{comb}_t}) \), \( L_{\text{comb}} \) is a set of levels of confidence of combining the solutions of CBR and RBR, \( L_{\text{comb}} = (L_{\text{comb}_1}, L_{\text{comb}_2}, \ldots, L_{\text{comb}_t}) \), \( t \) is the number of distinct conclusions of combining the solutions of CBR and RBR, \( C_{\text{comb}_i} \) is a symbolic value and the \( i \)-th conclusion of \( C_{\text{comb}} \), \( I_{\text{comb}_i} \) is a numerical value and the \( i \)-th intensities of \( I_{\text{comb}} \), \( L_{\text{comb}_i} \) is a numerical value and the \( i \)-th level of confidence of \( L_{\text{comb}} \).

### 3.7.4 An illustration of the HCBR

To illustrate the proposed methodology of combination of CBR and RBR, the following example is considered. A simplified case base is given in Table 3.3. The types of value of “Age”, “Gender”, “Motivation” and “Symptoms” are numerical value, symbolic value, fuzzy value and multi-symbolic value, respectively. The fuzzy set of the field “Motivation” is the same as the fuzzy set of Intensity which is
shown in Figure 3.21. A simplified rule base is shown as follows.

**R1:** IF <Gender = M> THEN <Join activity "A"> WITH <Intensity "Medium"> WEIGHT <0.5>

**R2:** IF <Motivation = High> THEN <Join activity "A"> WITH <Intensity "High"> WEIGHT <0.8>

**R3:** IF <Gender = F> THEN <Join activity "D"> WITH <Intensity "High"> WEIGHT <0.7>

**R4:** IF <Symptoms Contain Euphoric Mood> THEN <Join activity "B"> WITH <Intensity "Low"> WEIGHT <0.6>

<table>
<thead>
<tr>
<th>Case No.</th>
<th>Age</th>
<th>Gender</th>
<th>Motivation</th>
<th>Symptoms</th>
<th>Solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15</td>
<td>M</td>
<td>High</td>
<td>Delusion; Euphoric mood</td>
<td>Join activities &quot;A&quot; and &quot;B&quot; with intensities 0.75 and 0.5 respectively</td>
</tr>
<tr>
<td>2</td>
<td>17</td>
<td>F</td>
<td>Low</td>
<td>Weight loss; Paranoid; Euphoric mood</td>
<td>Join activities &quot;D&quot; and &quot;E&quot; with intensities 0.5 and 0.5 respectively</td>
</tr>
<tr>
<td>3</td>
<td>18</td>
<td>M</td>
<td>Low</td>
<td>Euphoric mood; Visual hallucinations</td>
<td>Join activities &quot;B&quot; and &quot;C&quot; with intensities 0.25 and 0.5 respectively</td>
</tr>
</tbody>
</table>

Table 3.3: A simplified case base

It is assumed that all the weightings for CBR and Combination are the same.

The minimum and maximum values for age are 12 and 25, respectively. In addition, it is assumed that there is a new case which has the following attributes:

{Age: 14

Gender: M

Motivation: Medium

Symptoms: Delusion; Euphoric mood}
Figure 3.21: Fuzzy set of motivation and joining activity intensity

By applying Equation (3.20), the similarities between the new case and the cases in the case base are given in Table 3.4. $s_{ij}$ is the similarity between the $i$-th feature of the new case and the $j$-th case in the case base. $S_j$ is the similarity measure between the new case and the $j$-th case in the case base. From Table 3.4, case 1 obtains the highest similarity. Thus, the solution of CBR = {(Activity A, Activity B), (High, Medium), 0.77}.

**Table 3.4: Results of the CBR**

<table>
<thead>
<tr>
<th>$j$</th>
<th>$s_{1j}$</th>
<th>$s_{2j}$</th>
<th>$s_{3j}$</th>
<th>$s_{4j}$</th>
<th>$S_j$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.92</td>
<td>1</td>
<td>0.14</td>
<td>1</td>
<td>0.77</td>
</tr>
<tr>
<td>2</td>
<td>0.77</td>
<td>0</td>
<td>0.14</td>
<td>0.25</td>
<td>0.29</td>
</tr>
<tr>
<td>3</td>
<td>0.69</td>
<td>1</td>
<td>0.14</td>
<td>0.33</td>
<td>0.54</td>
</tr>
</tbody>
</table>

By comparing the new case with the rules in the simplified rule base, R1, R2 and R4 are fired. By applying Equations (3.22) to (3.24):

$$C_{rbr} = (\text{Activity A}) \cup (\text{Activity A}) \cup (\text{Activity B}) = (\text{Activity A, Activity B}) \quad (3.33)$$
Chapter 3 Computational Narrative Simulation (CNS)

\[ I_{rbr} = \text{Merge}_r(\text{Medium, High, Low}) = (\text{High, Low}) \]  
(3.34)

\[ L_{rbr} = \text{Merge}_l(0.5, 0.8, 0.6) = (0.8, 0.6) \]  
(3.35)

Thus, the solution of RBR = \{(Activity A, Activity B), (High, Low), (0.8, 0.6)\}.

By applying Equations (3.25) to (3.31):

\[ C_{comb} = (\text{Activity A, Activity B}) \cup (\text{Activity A, Activity B}) = (\text{Activity A, Activity B}) \]  
(3.36)

\[ I_{comb} = \left( \frac{1 \times 0.77 + 1 \times 0.8}{1 + 1}, \frac{1 \times 0.77 + 1 \times 0.6}{1 + 1} \right) = (0.79, 0.69) \]  
(3.37)

\[ I_{comb} = \left( \frac{1 \times 0.77 \times 0.75 + 1 \times 0.8 \times 0.75}{1 \times 0.77 + 1 \times 0.8}, \frac{1 \times 0.77 \times 0.5 + 1 \times 0.6 \times 0.25}{1 \times 0.77 + 1 \times 0.6} \right) = (0.75, 0.39) \]  
(3.38)

Thus, the solution of combining CBR and RBR = \{(Activity A, Activity B), (0.75, 0.39), (0.79, 0.69)\}.

3.8 Self associated concept mapping (SACM)

After the generation of decision choices by the HCBR in the NSCS, SACM is used to associate the relevant concepts related to each choice, so as to create the multi-linear narrative. SACM has a knowledge representation which is similar to attributed concept maps (ACM) (Chen et al, 2001). Contrasting to manually constructed ACM, SACM can be automatically constructed and dynamically updated from a knowledge repository with structured historical records. SACM makes use of fuzzy set theory on dividing the concepts within the historical records. A new model named Constrained Fuzzy Spreading Activation (CFSA) is used for the manipulation of SACM. CFSA integrates fuzzy logic and Constrained Spreading Activation (CSA)
(Crestani and Lee, 2000) so as to provide more precise, rapid and automatic solutions.

### 3.8.1 Knowledge representation of the SACM

The graphical representation provides insights for describing the relationships among different knowledge concepts. A SACM is represented by a simple graph with nodes and edges. The nodes represent concepts relevant to a given domain and the association relationships between them are depicted by directed edges. An example of SACM is shown in Figure 3.22. The importance of the concepts and the associations between different concepts are indicated by the depth of color i.e. darker color indicates higher importance.

![Figure 3.22: An example of the SACM](image)

A SACM is defined with all necessary notations as follows:

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

### 3.8.2 Knowledge elicitation of the SACM

With the advanced development of computer technology and knowledge-based systems (KBS) in the present decade, organizations are able to record the working activities of each worker at a dramatically lower cost. Some KBSs have been developed to serve this purpose. The knowledge of knowledge workers can be assimilated and stored in a structured format into the knowledge repositories of KBSs when they use the KBSs for performing their daily work. This makes available vast new mines of information on individual working knowledge automatically and objectively. By following the learning theory, individuals’ abilities to work depend on whether they have an appropriate concept map of working. In the SACM, the concept map of each individual is constructed based on the information in the knowledge repositories of the KBS and dynamic updating is made possible by adding new records to the knowledge repository.

As shown in Figure 3.23, the elicitation algorithm consists of 3 major steps:
(i) Step 1: A temporary SACM is constructed based on the information of the new record.

Figure 3.23: Knowledge elicitation of the SACM

- Distinct concepts are extracted from the new record for the construction of a set of concept nodes $C$ and the degree of importance of concept $F_i$ for each $C_i \in C$ is assigned by the following conditions:

Let $S$ be the set of fields of the knowledge repository, and $V$ be the set of values of fields of the new record, where $V_i$ corresponds to $S_i$ for $V_i \in V$ and $S_i \in S$.

If $V_i$ is a symbolic value, a concept node is added as a text value in the format of $S_i : V_i$, and the corresponding degree of importance of the added concept is assigned to be 1. For example, if $S_i =$ “Product Type” and $V_i =$
“Mould Insert”, then a new concept node “Product Type: Mould Insert” is added to $C$, and the corresponding degree of importance of added concept $F = 1$

If $V_i$ is a numerical value, $V_i$ is fuzzified based on the corresponding membership function of $S_i$, concept node(s) is/are added as text value(s) in the format of $S_i: V_i$’s belonged membership(s), and the corresponding degree(s) of importance of the added concept(s) is/are assigned to be the corresponding degree(s) of membership. For example, if $S_i = “Quantity”$ and $V_i = (0.7 \text{ High}, 0.2 \text{ Medium}, 0 \text{ Low})$, then two new concept nodes: “Quantity: High” and “Quantity: Medium” are added to $C$, the corresponding degree of importance of the added concepts $F = 0.7$ of concept “Quantity: High” and $F = 0.2$ of concept “Quantity: Medium”

- Assign the degree of importance of relation $L_{ij}$ for each pair of concepts $(C_i, C_j)$, where $i, j \in n$ and $n$ is the total number of distinct concepts $C$, by the following equation:

$$L_{ij} = \text{Min}(V_i, V_j) \tag{3.39}$$

(ii) Step 2: Combining the temporary SACM with the original SACM

- The nodes and relations of the temporary SACM are matched with that of the original SACM. If any concepts are missing, the degree of importance of that concept and the degrees of importance of that concept’s associated relations are assigned to be 0

- The degrees of importance of the concepts $L$ and the degrees of relation $F$ of the original SACM are adjusted based on $L$ and $F$ of the
temporary SACM by the following equations:

Let $F_i, F'_i, F''_i$ be the original, temporary and combined degree of
importance of $C_i$, $N$ be the total number of records of the original SACM.

For $N > 0$, $F''_i = \frac{F'_i + N F_i F_{\max}}{N + 1}$ \hspace{1cm} (3.40)

For $N = 0$, $F''_i = F'_i$ \hspace{1cm} (3.41)

Let $L_{ij}, L'_{ij}, L''_{ij}$ be the original, temporary and combined degree of
relations between $C_i$ and $C_j$, $N$ be the total number of records of the
original SACM.

For $N > 0$, $L''_{ij} = \frac{L'_i + N L_i L_{\max}}{N + 1}$ \hspace{1cm} (3.42)

For $N = 0$, $L''_{ij} = L'_i$ \hspace{1cm} (3.43)

(iii) Step 3: The parameters of the combined SACM is adjusted and the combined
SACM is normalized.

- The parameters of the combined SACM, $P = (F_{\max}, L_{\max}, N)$, is adjusted by
the following equations:

\[
F_{\max} = \text{Max}(F_1, F_2, ..., F_n) \hspace{1cm} (3.44)
\]

\[
L_{\max} = \text{Max}(L_1, L_2, ..., L_n) \hspace{1cm} (3.45)
\]

- The total number of record $N$ is increased by 1

- $L$ and $F$ of the combined SACM is normalized to the range between 1
and 0 by the following equations:

\[
\text{Normalize}(F) = \frac{F}{F_{\max}} \hspace{1cm} (3.46)
\]
Chapter 3 Computational Narrative Simulation (CNS)

\[ \text{Normalize}(L) = \frac{L}{L_{\text{max}}} \]  

(3.47)

3.8.3 Knowledge inference of the SACM

A new model named Constrained Fuzzy Spreading Activation (CFSA) which integrates fuzzy logic and CSA is introduced for knowledge inference. As shown in Figure 3.24, the knowledge inference of SACM consists of 3 steps:

(i) Step 1: The enquiry/problem is converted into SACM format
   - This step is the same as step 1 of knowledge elicitation.

(ii) Step 2: The activation level of each node of the SACM is computed. This is then used for performing knowledge inference
   - The nodes and relations of enquired SACM are matched with that of SACM that was used for performing knowledge inference. If there is any concept missing, the degree of importance of that concept and the degrees of importance of that concept’s associated relations are assigned to be 0
   - The activation level of each node of the SACM is computed based on the degree of importance of the nodes and relations by the following equations:
     
     Let \( M' = (C', F', L', P') \) be the enquired SACM, and \( M = (C, F, L, P) \) be the SACM that are used for performing knowledge inference, \( A_j \) be the activation level of node \( j \)
     
     \[ A_j = \sum_i F'_i F_i L_{ij} \]  

(3.48)

(iii) Step 3: Generation of the result
   - The concept nodes of the result field are extracted and their corresponding
activation levels are calculated based on the following conditions:

If the extracted concept node is a fuzzy value, its consequent membership function at the level of corresponding activation level of that concept node is clipped. Then the clipped membership function is aggregated into a single fuzzy set. The fuzzy set is then defuzzified by the centre of gravity (COG) method and the result is displayed. The COG of fuzzy set $A$ on the interval $a_1$ to $a_2$ with membership function $\mu_A$ is given by the following equation:

$$
COG(A) = \frac{\int_{a_1}^{a_2} \mu_A(x)dx}{\int_{a_1}^{a_2} \mu_A(x)dx}
$$

(3.49)

If the extracted concept node is symbolic, the concept node with the highest activation level is selected to be the result.

---

![Diagram](#)

Figure 3.24: Knowledge inference of the SACM
3.8.4 An illustrative example of the SACM

An example is used to illustrate the application of SACM. This is a simple example to show how a SACM is constructed and how a SACM infers quantitative prediction. Table 3.5 shows a simplified knowledge repository that stores 2 quotation records. Each record includes a Case ID, Product Type, Diameter and Unit Price. Case ID provides a unique index of the records. Product Type contains symbolic values. Diameter and Unit Price contain numerical values.

Table 3.5: A simplified knowledge repository

<table>
<thead>
<tr>
<th>Case ID</th>
<th>Product type</th>
<th>Diameter</th>
<th>Unit Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Prototype Lens</td>
<td>7</td>
<td>1400</td>
</tr>
<tr>
<td>2</td>
<td>Mould Insert</td>
<td>12</td>
<td>2000</td>
</tr>
</tbody>
</table>

The membership functions of Diameter and Unit Price are shown in Figures 3.25 and 3.26, respectively. In this example, Diameter is represented by 3 fuzzy regions which are Small, Medium and Large. The Unit Price is represented by 3 fuzzy regions which are Low, Medium and High.

Figure 3.25: The membership functions of diameter
In order to construct a new SACM, all distinct concepts from the first record are firstly extracted for the construction of a set of concept nodes \( C \), the set of degrees of importance of concept \( F \) are assigned, and the set of degrees of importance of relations \( L \) for each pair of concepts are assigned, based on the step 1 of knowledge elicitation. The results are shown in Table 3.6. In step 2, since it is the first record to be assimilated, there is no original SACM (i.e. \( N = 0 \)). Thus, \( F \) and \( L \) are kept the same. In step 3, \( F \) and \( L \) are normalized, and the parameters of \( P = (F_{\text{max}}, L_{\text{max}}, N) \) are assigned. The results are shown in Table 3.7 and the graphical representation is depicted in Figure 3.27.

Table 3.6: Temporary results of the SACM that assimilates 1 record

<table>
<thead>
<tr>
<th>( i )</th>
<th>( C_i )</th>
<th>( F_i )</th>
<th>( L_0 )</th>
<th>( C_1 )</th>
<th>( C_2 )</th>
<th>( C_3 )</th>
<th>( C_4 )</th>
<th>( C_5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Product Type:Prototype Lens</td>
<td>1</td>
<td>( C_1 )</td>
<td>0</td>
<td>0.6</td>
<td>0.4</td>
<td>0.2</td>
<td>0.8</td>
</tr>
<tr>
<td>2</td>
<td>Diameter:Small</td>
<td>0.6</td>
<td>( C_2 )</td>
<td>0.6</td>
<td>0</td>
<td>0.4</td>
<td>0.2</td>
<td>0.6</td>
</tr>
<tr>
<td>3</td>
<td>Diameter:Medium</td>
<td>0.4</td>
<td>( C_3 )</td>
<td>0.4</td>
<td>0.4</td>
<td>0</td>
<td>0.2</td>
<td>0.4</td>
</tr>
<tr>
<td>4</td>
<td>Unit Price:Low</td>
<td>0.2</td>
<td>( C_4 )</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0</td>
<td>0.2</td>
</tr>
<tr>
<td>5</td>
<td>Unit Price:Medium</td>
<td>0.8</td>
<td>( C_5 )</td>
<td>0.8</td>
<td>0.6</td>
<td>0.4</td>
<td>0.2</td>
<td>0</td>
</tr>
</tbody>
</table>
Table 3.7: Results of the SACM that assimilates 1 record

| \( i \) | \( C_i \) | \( F_i \) | \( L_{ij} \) | \( C_1 \) | \( C_2 \) | \( C_3 \) | \( C_4 \) | \( C_5 \) |
|---|---|---|---|---|---|---|---|
| 1 | Product Type: Prototype Lens | 1 | \( C_1 \) | 0 | 0.75 | 0.5 | 0.25 | 1 |
| 2 | Diameter: Small | 0.6 | \( C_2 \) | 0.75 | 0 | 0.5 | 0.25 | 0.75 |
| 3 | Diameter: Medium | 0.4 | \( C_3 \) | 0.5 | 0.5 | 0 | 0.25 | 0.5 |
| 4 | Unit Price: Low | 0.2 | \( C_4 \) | 0.25 | 0.25 | 0.25 | 0 | 0.25 |
| 5 | Unit Price: Medium | 0.8 | \( C_5 \) | 1 | 0.75 | 0.5 | 0.25 | 0 |

\[ P = (F_{max} = 1, L_{max} = 0.8, N = 1) \]

Figure 3.27: The SACM that assimilates 1 record

To illustrate how to assimilate new records to the existing SACM, the following illustration is considered. Step 1 is similar to the previous section, the set of concept nodes \( C \) of the new record, the set of degrees of importance of concept \( F \) of the new record, and the set of degrees of importance of relations \( L \) for each pair of concepts of the new record are assigned (i.e. the second record). The results are shown in Table 3.8.

In step 2 of knowledge elicitation, the nodes and relations of the current SACM is matched with that of the previous SACM. For any identified missing concept, the degree of importance of that concept and the degrees of importance of that concept’s
associated relations are assigned to 0. Then \( F \) and \( L \) of the 2 SACMs are combined by Equations (3.40) and (3.42).

Table 3.8: Temporary results of the SACM that assimilates the second record

<table>
<thead>
<tr>
<th>( i )</th>
<th>( C_i )</th>
<th>( F_i )</th>
<th>( L_{ij} )</th>
<th>( C_1 )</th>
<th>( C_2 )</th>
<th>( C_3 )</th>
<th>( C_4 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Product Type:Mould Insert</td>
<td>1</td>
<td>( C_1 )</td>
<td>0</td>
<td>0.6</td>
<td>0.4</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>Diameter:Medium</td>
<td>0.6</td>
<td>( C_2 )</td>
<td>0.6</td>
<td>0</td>
<td>0.4</td>
<td>0.6</td>
</tr>
<tr>
<td>3</td>
<td>Diameter:Large</td>
<td>0.4</td>
<td>( C_3 )</td>
<td>0.4</td>
<td>0.4</td>
<td>0</td>
<td>0.4</td>
</tr>
<tr>
<td>4</td>
<td>Unit Price:Medium</td>
<td>1</td>
<td>( C_4 )</td>
<td>1</td>
<td>0.6</td>
<td>0.4</td>
<td>0</td>
</tr>
</tbody>
</table>

The result is shown in Table 3.9. \( M = (C, F, L, P) \) is the previous SACM that assimilates record 1 while \( M' = (C', F', L', P') \) is the current SACM that assimilates record 1. Hence, \( M'' = (C'', F'', L'', P'') \) is the combined SACM. In step 3, the combined SACM is normalized, and the parameters are assigned. The results are shown in Table 3.10 and the graphical representation is shown in Figure 3.28.

Figure 3.28: SACM that assimilates 2 records
To illustrate how to infer an enquiry in order to use SACM to perform a quantitative prediction, it is assumed that there is an enquiry requesting the Unit
Price of \{\text{Product Type: Prototype Lens, Diameter: } 9\}, and the SACM that is constructed above is used as the inference SACM. Based on the steps of knowledge inference, the enquiry is firstly converted into SACM format. The results are shown in Table 3.11.

Table 3.10: Results of the SACM that assimilates 2 records

<table>
<thead>
<tr>
<th>( i )</th>
<th>( C_i )</th>
<th>( F_i )</th>
<th>( L_{ij} )</th>
<th>( C_1 )</th>
<th>( C_2 )</th>
<th>( C_3 )</th>
<th>( C_4 )</th>
<th>( C_5 )</th>
<th>( C_6 )</th>
<th>( C_7 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Product Type: Prototype Lens</td>
<td>0.56</td>
<td>0.6</td>
<td>0.4</td>
<td>0.2</td>
<td>0.8</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Diameter: Small</td>
<td>0.33</td>
<td>0.6</td>
<td>0</td>
<td>0.4</td>
<td>0.2</td>
<td>0.6</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Diameter: Medium</td>
<td>0.56</td>
<td>0.4</td>
<td>0.4</td>
<td>0</td>
<td>0.2</td>
<td>1</td>
<td>0.6</td>
<td>0.4</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Unit Price: Low</td>
<td>0.11</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Unit Price: Medium</td>
<td>1</td>
<td>0.8</td>
<td>0.6</td>
<td>1</td>
<td>0.2</td>
<td>0</td>
<td>1</td>
<td>0.4</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Product Type: Mould Insert</td>
<td>0.56</td>
<td>0</td>
<td>0</td>
<td>0.6</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0.4</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Diameter: Large</td>
<td>0.22</td>
<td>0</td>
<td>0</td>
<td>0.4</td>
<td>0</td>
<td>0.4</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

\( P = (F_{\text{max}} = 0.9, L_{\text{max}} = 0.5, N = 2) \)

Table 3.11: The SACM of the example of enquiry

<table>
<thead>
<tr>
<th>( i )</th>
<th>( C_i )</th>
<th>( F_i )</th>
<th>( L_{ij} )</th>
<th>( C_1 )</th>
<th>( C_2 )</th>
<th>( C_3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Product Type: Prototype Lens</td>
<td>1</td>
<td>0</td>
<td>0.2</td>
<td>0.8</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Diameter: Small</td>
<td>0.2</td>
<td>0.2</td>
<td>0</td>
<td>0.2</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Diameter: Medium</td>
<td>0.8</td>
<td>0.8</td>
<td>0.2</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

In step 2, the enquiry SACM is matched with the assimilated SACM. The activation level of each concept is then computed by Equation (3.48). The results are shown in Table 3.12. In step 3, the concepts of the result field (i.e. Unit Price) and their corresponding activation levels are extracted (i.e. Unit Price:Low:0.21, Unit Price:Medium:0.93). The consequent membership functions at the level of corresponding activation levels are then clipped and aggregated as shown in Figure 3.29. The aggregated fuzzy set is then defuzzified by Equation (3.49), the result is
Thus, the suggested Unit Price of the enquiry is 1816.

Table 3.12: Activation level of each concept of this example

<table>
<thead>
<tr>
<th>i</th>
<th>$C_i$</th>
<th>$A_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Product Type:Prototype Lens</td>
<td>0.22</td>
</tr>
<tr>
<td>2</td>
<td>Diameter:Small</td>
<td>0.51</td>
</tr>
<tr>
<td>3</td>
<td>Diameter:Medium</td>
<td>0.25</td>
</tr>
<tr>
<td>4</td>
<td>Unit Price:Low</td>
<td>0.21</td>
</tr>
<tr>
<td>5</td>
<td>Unit Price:Medium</td>
<td>0.93</td>
</tr>
<tr>
<td>6</td>
<td>Product Type:Mould Insert</td>
<td>0.27</td>
</tr>
<tr>
<td>7</td>
<td>Diameter:Large</td>
<td>0.18</td>
</tr>
</tbody>
</table>

Figure 3.29: An aggregated fuzzy set of this example

3.9 Summary

To realize the automatic construction of narrative simulation and integration of knowledge management processes into the daily workflow of the knowledge workers, a Computational Narrative Simulation (CNS) approach is presented and a Computational Narrative Simulation System (CNSS) is designed and built which is composed of a knowledge-based system (KBS) and a narrative simulation construction system (NSCS). The KBS and NSCS are supported by a knowledge repository (KR) and four major computational intelligent algorithms which are fuzzy associated concept mapping (FACM), hybrid case-based reasoning (HCBR),
self-associated concept mapping (SACM) and a narrative prediction and construction algorithm.

The CNSS supports knowledge creation, storage, sharing, and application for achieving OL. It provides a decision support application for workers’ daily operations. Knowledge created can be distributed easily through the user-friendly system interface, which facilitates information searching and knowledge sharing. Individuals are supported with the shared knowledge of the organization, and vice versa, shared knowledge is contributed by individuals. Workers’ contexts are continuously being aligned and this helps the organization to achieve the most economic level of abstraction of knowledge sharing (Snowden, 2000, 2000c).

Furthermore, the organizational knowledge is continuously replenished by the dynamic update of individual and shared knowledge. Moreover, the CNSS enables narrative simulation to be created at any time and at any place. Past narrative knowledge are consolidated to form a new narrative. People can try out their actions through the narrative simulation, which enables learning in a way that is cost effective, fast, appropriate, flexible, and ethical. It minimizes the human effort as compared with the traditional construction methods which are based on manual operations. Through the narrative simulation, workers learn and improve their problem solving skills. The predictive function of the method enables workers to learn proactively and provides extra time for users to rethink their work, which increases the quality of their problem-solving skills and methods.

In this chapter, the research methodology for CNS and the establishment of
CNSS are presented. The design of the KBS and NSCS are elaborated. The theoretical base and working principles for a series of the computational intelligent algorithms are presented for supporting the CNS. These algorithms are original and contribute significantly to advancement of technology for narrative simulation. They attempt to address the limitations and deficiencies of existing algorithms as reviewed in Chapter 2. The performance of each algorithm of the CNSS is evaluated by comparing with different inference and reasoning methodologies in Chapter 4. The application of the system is demonstrated in Chapter 5 by a trial implementation in a selected reference site in the social service industry. A case study is used to measure the performance of the system. Moreover, a controlled experiment is also carried out for measuring the learning outcome of the system.
In this chapter, the computational intelligent algorithms used in the computational narrative simulation system (CNSS) are evaluated quantitatively. They include fuzzy associated concept mapping (FACM), narrative prediction and construction, hybrid case-based reasoning (HCBR), and self-associated concept mapping (SACM).

4.1 Experimental verification for the FACM

The evaluation focuses on the automatic process of the FACM, testing the algorithm’s performance by extracting a list of propositions for constructing a concept map. The experimental flow is shown in Figure 4.1.

![Experimental flow of the FACM evaluation](image)

Figure 4.1: Experimental flow of the FACM evaluation

Each document is processed individually and its propositions are automatically extracted using the working principles described in Chapter 3. The present study makes use of the scientific abstracts collected from the journal of Information...
A total of 18 abstracts of the journal papers and 10 technology news articles are selected for extracting propositions for the evaluation. The evaluation is then based on matching between the identified propositions by expert groups and the set of propositions generated by the system. The results are measured by precision and recall of the number of valid propositions (i.e. the exact matching of concept-relationship-concept format).

The performance of the FACM is compared with a baseline algorithm which adopts a natural language processing tool named ANNIE (A Nearly-New Information Extraction System) by using the platform GATE (General Architecture for Text Engineering) (Cunningham, et. al., 2002). The back end of the baseline system includes several information extraction components which include an English tokenizer, a gazetteer, a sentence splitter and a POS tagger. The flow of extraction starts from the English tokenizer which is used to recognize the basic tokens, i.e.,
words. Gazetteer is used to recognize the special terms of the domain such as number, day, etc. Sentence splitter and POS tagger are used to tag each token with its correct part-of-speech. Lastly, the noun-verb-noun patterns are extracted from each sentence of the texts.

Figure 4.2 depicts a screenshot of the application of the FACM. After inputting the texts of the abstracts of the journal papers, a concept map is automatically constructed. For example, one input text is “The term mismatch problem in information retrieval is a critical problem, and several techniques have been developed, such as query expansion, cluster-based retrieval and dimensionality reduction to resolve this issue. Of these techniques, this paper performs an empirical study on query expansion and cluster-based retrieval. We examine the effect of using parsimony in query expansion and the effect of clustering algorithms in cluster-based retrieval. In addition, query expansion and cluster-based retrieval are compared, and their combinations are evaluated in terms of retrieval performance by performing experimentations on seven test collections of NTCIR and TREC.” (Na, et al., 2007). The output propositions are shown in Table 4.1.

Figure 4.2: Screenshot of the application of the FACM
Table 4.1: Output propositions of the sample text

<table>
<thead>
<tr>
<th>Proposition ID</th>
<th>Concept</th>
<th>Relationship</th>
<th>Concept</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>term mismatch problem in information retrieval</td>
<td>is</td>
<td>critical problem</td>
</tr>
<tr>
<td>2</td>
<td>term mismatch problem in information retrieval</td>
<td>such as</td>
<td>query expansion</td>
</tr>
<tr>
<td>3</td>
<td>term mismatch problem in information retrieval</td>
<td>such as</td>
<td>cluster-based retrieval</td>
</tr>
<tr>
<td>4</td>
<td>term mismatch problem in information retrieval</td>
<td>such as</td>
<td>dimensionality reduction</td>
</tr>
<tr>
<td>5</td>
<td>this paper</td>
<td>performs</td>
<td>empirical study on query expansion</td>
</tr>
<tr>
<td>6</td>
<td>this paper</td>
<td>performs</td>
<td>cluster-based retrieval</td>
</tr>
<tr>
<td>7</td>
<td>We</td>
<td>examine</td>
<td>effect of using parsimony in query expansion</td>
</tr>
<tr>
<td>8</td>
<td>We</td>
<td>examine</td>
<td>effect of clustering algorithms in cluster-based retrieval</td>
</tr>
<tr>
<td>9</td>
<td>their combinations</td>
<td>are evaluated in terms of</td>
<td>retrieval performance</td>
</tr>
</tbody>
</table>

The results are shown in Figure 4.3, Figure 4.4 and Table 4.2. The results suggest that the algorithm increases recall rate and maintains a high precision rate when compared with the baseline. Since the baseline algorithm extracts only one noun-verb-noun pattern for each sentence, the recall rate is much lower than FACM. The proposed anaphoric resolution increased the overall performance. An average recall rate of over 78% for scientific abstracts and over 74% of technology news was achieved.

As shown in Figures 4.5 and 4.6, the recall rate and precision rate are measured against the word count of the articles. The average word count for the abstracts and news are 140 and 268, respectively. Although the results show that the accuracy of
the method decreases gradually with increasing length of the text, it is highly accurate for analyzing documents with a length of up to 400 words. Such kind of documents are commonly found in various information sources such as abstract databases, emails, discussion forums, news groups, on-line communities, etc. As a whole, the algorithm successfully associates the documents with the original propositions. This is promising for its use as the basic domain independent algorithm for extracting propositions.

Figure 4.3: Recall and precision of the baseline and the FACM (Abstracts)

Figure 4.4: Recall and precision of the baseline and the FACM (News)
Table 4.2: Evaluation results of the FACM

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>Proposed Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Precision (Abstracts)</td>
<td>86.7 %</td>
<td>87.2 %</td>
</tr>
<tr>
<td>Average Recall (Abstracts)</td>
<td>36.2 %</td>
<td>78.3 %</td>
</tr>
<tr>
<td>Average Precision (News)</td>
<td>82.6 %</td>
<td>83.0 %</td>
</tr>
<tr>
<td>Average Recall (News)</td>
<td>39.8 %</td>
<td>74.3 %</td>
</tr>
</tbody>
</table>

Figure 4.5: Recall and precision of the FACM against word count (Abstracts)

Figure 4.6: Recall and precision of the FACM against word count (News)
4.2 Experimental verification for the narrative prediction and construction

The capability of the narrative prediction and construction algorithm is evaluated through a trial implementation for managing the unstructured knowledge in a department of a social service organization in Hong Kong. The department selected for the implementation of the present study is responsible for providing services of early intervention for the purpose of mental healthcare among adolescents. A lot of information needs to be recorded for every single case, including personal data, mental health assessment, development history, history of suicide, family background, treatment records, review records, etc. The department has implemented a workflow management system for managing its case knowledge.

Due to the characteristics of the domain which is full of fragmentary narrative data, it is difficult to retain the information entirely in a structured format. The massive amount of unstructured text data makes it extremely difficult to analyze. The previous system mainly served as a workflow system, a reporting system, and a database system for storing its clients’ information. Actual knowledge sharing and reuse among the workers, particularly new unstructured knowledge, is still limited. During the case management of the organization, a caseworker interviews a client and carries out diagnostic assessment for evaluating the client’s mental health status. The caseworker is required to write a small narrative into the system to describe the current problem of the client. Faced with the problem presented at the interview, the caseworker needs to derive a treatment plan and help the client to establish the determined goals.

In the present study, the existing system was further developed to accomplish
and verify the proposed methodology by making use of the stored narratives of the problems presented by clients. Firstly, the narratives are converted into concept maps by the FACM. Table 4.3 shows the results of the conversion of a sample text into a concept map. The text is “Client has impairment of functioning, social anxiety, avoidant behaviour, and depressive symptoms, such as sleep disturbances, loss of energy, fleeting suicidal ideas, worthless ideas, and hopeless ideas. Impairment of functioning includes social relationship, and working relationship. Client does not have psychotic features identification.” and the concept map is generated as shown in Figure 4.7.

<table>
<thead>
<tr>
<th>Concept</th>
<th>Relationship</th>
<th>Concept</th>
</tr>
</thead>
<tbody>
<tr>
<td>client</td>
<td>have</td>
<td>impairment of functioning</td>
</tr>
<tr>
<td>client</td>
<td>have</td>
<td>social anxiety</td>
</tr>
<tr>
<td>client</td>
<td>have</td>
<td>avoidant behaviour</td>
</tr>
<tr>
<td>client</td>
<td>Have</td>
<td>depressive symptoms</td>
</tr>
<tr>
<td>depressive symptoms</td>
<td>such as</td>
<td>sleep disturbances</td>
</tr>
<tr>
<td>depressive symptoms</td>
<td>such as</td>
<td>loss of energy</td>
</tr>
<tr>
<td>depressive symptoms</td>
<td>such as</td>
<td>fleeting suicidal ideas</td>
</tr>
<tr>
<td>depressive symptoms</td>
<td>such as</td>
<td>worthless ideas</td>
</tr>
<tr>
<td>depressive symptoms</td>
<td>such as</td>
<td>hopeless ideas</td>
</tr>
<tr>
<td>Impairment of functioning</td>
<td>include</td>
<td>social relationship</td>
</tr>
<tr>
<td>Impairment of functioning</td>
<td>include</td>
<td>working relationship</td>
</tr>
<tr>
<td>client</td>
<td>does not have</td>
<td>psychotic features identification</td>
</tr>
</tbody>
</table>

Two experiments have been conducted. As shown in Figure 4.8, the evaluation used the unstructured text of treatment records of the organization as the testing data in the first experiment. There were 195 cases, and 512 paragraphs (about 19000 words) of treatment records. The evaluation is based on matching between the identified propositions by expert groups and the set of propositions generated by the algorithm. The results are measured by the precision and the recall of the number of
valid propositions (i.e. the exact matching of concept-relationship-concept format).

Encouraging results are obtained and they are shown in Figure 4.9, Figure 4.10 and Table 4.4. Even though the matching is so strict, it is interesting to note that over 90% of the average recall rate and precision are attained. In other words, the algorithm is capable of successfully associating the unstructured text with the original propositions. This is promising for its use as the basic domain independent algorithm to extract propositions.

Figure 4.7: An example of the resulted automatic concept map

Figure 4.8: Experimental flow of the narrative prediction evaluation
The second experiment is used to measure the accuracy of the prediction. There are 72 cases used in this experiment, which run from Oct 2004 to May 2006. As shown in Figure 4.8, the extracted propositions from the first experiment are...
clustered based on the assessment date of the case by certain time intervals, i.e. 1 month, 2 months, 3 months, 4 months, 5 months, and 6 months. The first quarter of the cases is classified as the training batch, and remaining cases are used as the testing batch, according to the date of the assessment. Based on the prediction model, it is firstly trained by the training batch in order to obtain the optimum values of the adaptation gain $\beta$, $a_{opt}(0)$, and $y_{opt}(0)$. Hence, the model is tested by the testing batch.

The performance of the model is measured by the averaged recall and precision of the number of correctly predicted propositions and concepts. The average recall for time interval $t$ is calculated by Equation (4.1).

$$recall_i = \frac{\sum_{j=1}^{m} C_{ni}}{mP_{ni}}$$

where $m$ is the total number of periods for time interval $t$, $C_{ni}$ is the number of correct predicted propositions (or concepts) for time interval $t$ at period $i$, and $P_{ni}$ is the number of propositions (or concepts) for time interval $t$ at period $i$.

Another recall measurement, $recall'_i$, excluding the consideration of new propositions is taken into account:

$$recall'_i = \frac{\sum_{j=1}^{m} C_{ni}}{m(P_{ni} - N_{ni})}$$

where $N_{ni}$ is the number of new propositions (or concepts) for time interval $t$ at period $i$ (i.e. the number of propositions (or concepts) that appeared in period $i$ the first time)
The average precision for time interval $t$ is calculated by the Equation (4.3):

$$\text{precision}_i = \sum_{i=1}^{m} \frac{C_i}{mR_i}$$  \hspace{1cm} (4.3)

where $R_i$ is the number of predicted propositions (or concepts) for time interval $t$ at period $i$.

Table 4.5 and Figures 4.11 to 4.16 show the experimental results. When the concepts and propositions that appeared the first time are excluded, it is interesting to note that there is a high recall rate in the prediction of both concepts and propositions. The results also show that the precision remains steady with the time. By considering the new concepts and propositions that appeared the first time, the recall is much lower. There is over 70% of accuracy in prediction of propositions when the time interval is set to 3 months or above. The accuracy is good even though the method of accuracy is determined under strict restriction and condition.

<table>
<thead>
<tr>
<th>Measurement</th>
<th>$t = 1$</th>
<th>$t = 2$</th>
<th>$t = 3$</th>
<th>$t = 4$</th>
<th>$t = 5$</th>
<th>$t = 6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>recall,$_i,$ (Concept)</td>
<td>50.70</td>
<td>64.00</td>
<td>65.45</td>
<td>74.43</td>
<td>80.39</td>
<td>79.56</td>
</tr>
<tr>
<td>precision,$_i,$ (Concept)</td>
<td>12.33</td>
<td>13.53</td>
<td>11.89</td>
<td>13.51</td>
<td>12.94</td>
<td>11.01</td>
</tr>
<tr>
<td>recall,$_i,$ (Proposition)</td>
<td>2.96</td>
<td>3.73</td>
<td>3.98</td>
<td>3.86</td>
<td>3.28</td>
<td>3.23</td>
</tr>
<tr>
<td>recall,$_i,$ (Proposition)</td>
<td>36.38</td>
<td>65.61</td>
<td>72.62</td>
<td>81.94</td>
<td>80.91</td>
<td>74.44</td>
</tr>
<tr>
<td>precision,$_i,$ (Proposition)</td>
<td>3.21</td>
<td>4.01</td>
<td>3.89</td>
<td>3.93</td>
<td>3.15</td>
<td>2.58</td>
</tr>
</tbody>
</table>
Chapter 4 Performance Evaluation for the Computational Intelligent Algorithms

Figure 4.11: Results of recall and precision for time interval is 1 month

Figure 4.12: Results of recall and precision for time interval is 2 months
Figure 4.13: Results of recall and precision for time interval is 3 months

Figure 4.14: Results of recall and precision for time interval is 4 months
Chapter 4 Performance Evaluation for the Computational Intelligent Algorithms

Figure 4.15: Results of recall and precision for time interval is 5 months

Figure 4.16: Results of recall and precision for time interval is 6 months
4.3 Experimental verification for the HCBR

The performance of the HCBR is evaluated by a series of real data experiments in the same social service organization as mentioned in Section 4.2. The case workflow involves different stages which include case workflow after intake, during assessment, and after review. There are more than 100 features in the case base and more than 20 rules in the rule base. The selection of features, rules, fuzzy membership functions and CBR weightings are determined by the expertise of the organization.

In the experiment, the weightings for combination are set to 1. As shown in Figure 4.17, 20 completed cases have been retained in the case base as the learning batch, and another 40 completed cases are prepared as the testing batch. The accuracy of solution among different methodologies (i.e. CBR, RBR and HCBR) at different stages of the case workflow (i.e. after intake, during assessment, and after review) is determined by Equations (4.4) and (4.5).

Figure 4.17: Experimental flow of the HCBR evaluation

Accuracy of intervention = Probability of correct intervention  \[ (4.4) \]
Accuracy of intensity = Probability of correct intensity on the condition that intervention is correct

\[(4.5)\]

The results are shown in Figures 4.18 to 4.23. It is interesting to note that the accuracy of the HCBR approach is higher than that of applying CBR or RBR separately. HCBR possesses a higher accuracy than CBR particularly when the number of learning cases is small. The accuracy of RBR maintains constant and it possesses a lower accuracy for intervention and a higher accuracy for intensity. The accuracy of CBR increases gradually and is similar to that of HCBR when the number of learning cases increases.

Figure 4.18: Results of HCBR, CBR and RBR in after intake (intervention)
During Assessment (Intervention)

Figure 4.19: Results of HCBR, CBR and RBR in during assessment (intervention)

After Review (Intervention)

Figure 4.20: Results of HCBR, CBR and RBR in after review (intervention)
Chapter 4 Performance Evaluation for the Computational Intelligent Algorithms

Figure 4.21: Results of HCBR, CBR and RBR in after intake (intensity)

Figure 4.22: Results of HCBR, CBR and RBR during assessment (intensity)
4.4 Experimental verification for the SACM

To evaluate the effectiveness of the SACM, two experiments have been carried out. One is dealing with structured data while the other one is dealing with unstructured narrative data. The former is applied in a consulting company which provides various consulting services in design, manufacture and evaluation of surface quality of precision optical components.

Table 4.6 shows the structure of the quotations in the company’s repository. The case number is assigned sequentially in order to provide a unique designation for each individual case. As different customers may be entitled to different privileges in terms of the customer services (e.g. discount, shorter delivery time, longer payment term, etc), the customer information is important to the decision making process. The product information is related to the product type, material,
geometry, quantity, requirements of inspection, and preparatory instruction of the machining jobs, etc. The decision is given in the form of a suggested quotation price, expected delivery date and payment method. When there is a request for a quotation, the customer will provide the product information, and then the staff needs to make the decision based on that information.

Table 4.6: The structure of a quotation in the knowledge repository

<table>
<thead>
<tr>
<th>Case number</th>
<th>Customer ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customer information</td>
<td>Customer ID</td>
</tr>
<tr>
<td>Staff information</td>
<td>Staff ID</td>
</tr>
<tr>
<td>Quotation date</td>
<td></td>
</tr>
<tr>
<td>Product information</td>
<td></td>
</tr>
<tr>
<td>Product type</td>
<td></td>
</tr>
<tr>
<td>Material</td>
<td></td>
</tr>
<tr>
<td>Diameter</td>
<td></td>
</tr>
<tr>
<td>Radius</td>
<td></td>
</tr>
<tr>
<td>Surface type</td>
<td></td>
</tr>
<tr>
<td>Quantity</td>
<td></td>
</tr>
<tr>
<td>Rough blank</td>
<td></td>
</tr>
<tr>
<td>Inspection</td>
<td></td>
</tr>
<tr>
<td>Decision</td>
<td>Unit price</td>
</tr>
<tr>
<td></td>
<td>Expected delivery date</td>
</tr>
<tr>
<td></td>
<td>Payment method</td>
</tr>
</tbody>
</table>

Figure 4.24: Experimental flow of the first SACM evaluation

As shown in Figure 4.24, SACM is compared with a CBR approach and a group of people who are laymen of the domain in the first experiment. In the CBR
approach, the new case is compared with all the cases in the knowledge repository. The similarity between two cases is determined by Equations (4.6):

\[
Similarity = \frac{\sum_{j=1}^{m} w_j sim(v_j^o, v_j^r)}{\sum_{j=1}^{m} w_j} \tag{4.6}
\]

where \( m \) is the number of inputs, \( w_j \) is the weighting of the \( j \)th input which are determined by the expertise of the company, \( v_j^o \) and \( v_j^r \) are values of the \( j \)th inputs and that for the retrieved cases, \( sim(v_j^o, v_j^r) \) is the similarity function for the \( j \)th inputs.

For numerical value, \( sim(v_j^o, v_j^r) \) is calculated based on the normalized distance of the features between two cases:

\[
sim(v_j^o, v_j^r) = 1 - \frac{|v_j^o - v_j^r|}{max_j - min_j} \tag{4.7}
\]

where \( max_j \) and \( min_j \) are the maximum and minimum value of the \( j \)th input.

For symbolic value:

\[
sim(v_j^o, v_j^r) = \begin{cases} 
1 & \text{if } v_j^o = v_j^r \\
0 & \text{if } v_j^o \neq v_j^r
\end{cases} \tag{4.8}
\]

The retrieved cases are ranked in descending order according to their similarity. The most similar case is then selected for giving suggestions. The accuracy of the suggested results is calculated by Equations (4.10):
a = \left( 1 - \frac{|v^s - v^r|}{v^r} \right) \times 100\% \quad (4.10)

where $a$ is the accuracy, $v^r$ is the actual value and, $v^s$ is the suggested value by the model.

In SACM, the fuzzy membership functions are determined by the expertise of the company. Initially, there is only one case is used as the learning record and another case is used as the testing record. After the model/human has answered the questions of the same testing record, the actual result of the testing record is provided. In other words, one new learning record is added to the knowledge base of the model/human (i.e. two learning records in the knowledge base of the model/human). Then, another testing record is provided.

The results of the average accuracy of SACM, CBR, and human against the number of learning records are shown in Figure 4.25 and Table 4.7. The results show that the accuracy of CBR is the highest and the accuracy of SACM is similar to the accuracy of humans. Based on the correlation analysis, SACM has a higher correlation with the result of laymen of the domain, while CBR has a higher correlation with the actual results (which is provided by an expert of the domain).

<table>
<thead>
<tr>
<th>Model</th>
<th>Average Accuracy</th>
<th>Correlation with human layman</th>
<th>Correlation with human expert</th>
</tr>
</thead>
<tbody>
<tr>
<td>SACM</td>
<td>83.27%</td>
<td>0.90</td>
<td>0.35</td>
</tr>
<tr>
<td>CBR</td>
<td>87%</td>
<td>0.69</td>
<td>0.47</td>
</tr>
<tr>
<td>Human layman</td>
<td>83.75%</td>
<td>1</td>
<td>0.36</td>
</tr>
<tr>
<td>Human expert</td>
<td>100%</td>
<td>0.36</td>
<td>1</td>
</tr>
</tbody>
</table>
Figure 4.25: The results of SACM, CBR and human

Another experiment has been carried out in the organization as mentioned in Section 4.2 which deals with unstructured narrative data. During the workflow of case management of the organization, a caseworker collects and analyzes the client’s situation, and then the caseworker is required to write a small narrative to describe the problem presented by the client. In the light of this problem, the caseworker needs to determine the treatment plan and helps the client to establish goals. After they have implemented the plan, the caseworker is required to write a small narrative to describe the review situation.

Figure 4.26: Experimental flow of the second SACM evaluation
The algorithm is evaluated by measuring the accuracy with which the review situation is inferred. The result is compared with the actual solution and the CBR approach. In the experimental setup, 100 cases are used as the learning batch, and 50 cases are used as the testing batch. Figure 4.26 shows the experimental flow of evaluation. Firstly, all the cases are converted into concept maps by the FACM. A case can be divided into two parts: problem and solution. The concepts of presenting problem and treatment plan are the problem part, and the concepts of review situation are the solution part. Each concept represents a concept node in SACM, and a feature in CBR. For CBR, the new case is compared with the learning batch in the knowledge repository. The setting of parameters is same as for the previous experiment for CBR and SACM.

The results of average accuracy of SACM, and CBR are 61.2% and 58.8% respectively. They are shown in Figure 4.27. It is interesting to note that the SACM and the CBR have a similar average accuracy. The accuracy of CBR is higher in the early stage while the number of learning cases is small. However, the accuracy of SACM increases significantly when the number of learning cases increases.

4.5 Summary

In this chapter, the four core algorithms of the computational narrative simulation system (CNSS) are evaluated. A series of experiments have been conducted for evaluating the performance of the algorithms. The performance of the fuzzy associated concept mapping (FACM) is measured by the precision rate and recall rate of the number of valid propositions using public databases. The results show that the FACM increases the recall rate (about 40% to 50% improvement) and
maintains a high precision rate (over 80%) when compared with the baseline algorithm.

The performance of the narrative prediction and construction algorithm was evaluated by measuring the accuracy of the predictive function in a social service organization with real cases. There is over 70% of accuracy in prediction of propositions when the time interval is set to 3 months or above. The accuracy is good even though the method of accuracy is determined under strict restriction and condition.

The performance of the hybrid case-based reasoning (HCBR) is evaluated by a series of real data experiments conducted in a social service organization dealing with treatment planning. The accuracies of solution among different methodologies (i.e. CBR, RBR and HCBR) at different stages of case workflow (i.e. after intake, during assessment, and after review) are measured. The results show that the
accuracy of the HCBR approach is higher than that of applying CBR (about 12% to 22% improvement) or RBR (about 3% to 47% improvement) separately.

The self-associated concept mapping (SACM) is evaluated against CBR, human experts and laymen of the domain. Two experiments have been carried out. One is dealing with structured data while the other one is dealing with unstructured narrative data. The results show that SACM possesses a higher correlation with laymen of the domain in structured data (0.90), and SACM achieve a higher accuracy in unstructured narrative data when the number of learning cases increases.

As a whole, the performance of the computational intelligent algorithms is good and well excels than some traditional and commercial available algorithms such as CBR and ANNIE, etc. The results form an important means for the evaluation of the performance and the capability of the computational narrative simulation (CNS) approach as well as the computational narrative simulation system (CNSS).
CHAPTER 5 IMPLEMENTATION AND CASE STUDY

The computational narrative simulation system has been evaluated through a case study at a selected reference site. A social service organization is selected as the reference site based on the assumptions mentioned in Section 3.4. The organizational learning environment is ready in the social service organization where the knowledge workers are willing to share and express their ideas in terms of narratives. A workflow system has been built for their daily operations for the case management. The workers of the organization are also willing to acquire the shared working practice so as to facilitate knowledge sharing and learning. The case study and results are described in this chapter.

5.1 Company background

Mental health problems have a serious impact on society. It is important to reduce the impact of mental disorders by identifying distress at an early age, establishing an early and accurate diagnosis and providing prompt and effective treatment. This idea underlies the interest in early intervention in mental disorders. Some countries have put this as a major element in their mental health policy (Kemp, 1993). Evidence from the many evaluation studies suggests that well-designed and intensive early intervention programs have the potential to yield outcomes that benefit health plans (e.g., improved health outcomes, lower health care costs, lower maternity costs, fewer ER visits) and/or outcomes that have potential benefits for Medicaid, the government, and society overall (e.g., higher educational attainment, greater economic self-sufficiency, lower crime rates). (Perloff et. al. 1998)
However, there is a variety of challenges faced by the mental health social service providers (Ferns, 1995). The increased need for services, decreased subvention for services due to economic restructuring and the attendant quest for budget cuts, and growing government regulation lead to the formulation of an immense pressure on social service agencies to provide effective, customized and high-quality care at the lowest cost and greater administrative control (Savage, 1987). The social service providers are facing the problem of conflict between these objectives. Limited resources must be traded off in order to accomplish any one objective over the other. Shrinking revenues have forced the social service providers to look for creative ways to provide quality services at less expense.

The computational narrative simulation system (CNSS) has been implemented in a social service organization in Hong Kong named Baptist Oi Kwan Social Service (BOKSS). The selected department is responsible for providing early intervention with mental healthcare services for adolescents. The organization was facing similar problems found in the social service domain, such as limited professionals, increasing workload, pressure from tight government funding, and unstructured and rapid growing case information.

5.2 Evaluation of the knowledge-based system (KBS)

After studying the workflow of the company and collecting the required information such as the information flow of the company, the case management process, the company expectations, etc, through studying the documents and conducting interviews, the user requirements were collected. Each case recorded contains lots of narrative information. This includes the personal data, mental health
As shown in Figure 5.1, the workflow of adolescent early intervention starts from case intake. The case may be referred from the client him/herself, client’s family, hospital, or from another social service centre. During the intake, information about the client’s personal details, previous clinical records, etc. are collected. A decision is then needed to be made to determine whether to accept the case or not. If the case is accepted, a caseworker is assigned to follow up the case. He/she interviews the client and carries out diagnostic assessment for evaluating the client’s mental status. Then, the caseworker needs to determine the treatment plan and helps the client to establish the determined goals. Each case is reviewed periodically in order to evaluate the progress and adjust the treatment plan. If the client’s condition is satisfactory, the case is terminated.

Figure 5.1: The workflow of adolescent early intervention
The traditional approach of treatment planning relies heavily on the experience of the caseworkers and the quality of treatment plans varies with the subjective views of the caseworkers. The good practice and know-how in treatment planning are also difficult to be shared effectively among the caseworkers. It is necessary to develop a KBS to improve knowledge sharing and increase working efficiency.

A KBS has been built which allows systematic handling of case information and supports the decision making process of the social workers. The system has undergone modification and customization according to the users’ feedback and it is now fully implemented in the adolescent early intervention case handling process. A snapshot of the workflow for managing a case is shown in Figure 5.2.

During the case management, workers can select the forms which need to be filled in. Every single case has records containing both structured and unstructured information. The records include information for describing the status of the client such as the personal data, mental health assessment, development history, suicide history, family background, treatment records, review records, etc. The interfaces of the forms are similar to the original paper forms they used before, so as to minimize staff learning time. After filling-in the forms, the workers can click “Suggestion” to view the suggestion provided by the system. The details of system interfaces can be found in Appendix E.

There are 7 case workers who are working in the adolescent early intervention program and they use the system in their case management. They are invited, through a questionnaire, to provide users’ feedback of the usage of the system. The
design of the questionnaire is based on the following dimensions:

(i) Customer satisfaction (willingness to use the new system. Is the system useful for them?)

(ii) Impact on service quality and efficiency (is the efficiency or service quality improved by comparing with implementing the KBS before?)

(iii) Resources required (hardware/ software, time, human resources)

(iv) Ease of use (is it easy to use/learn/set up/maintain?)

(v) Flexibility (Can it easily cope with developments in the future?)
The details of the questionnaire can be found in Appendix F. Their satisfactory level was rated from 1 to 5 (5 is highest agreement) on a Likert scale. The results obtained are shown in Figure 5.3. It is interesting to note that the users agree that the system can improve their work in the different dimensions as discussed above.

Figure 5.3: Results of users’ feedbacks on the proposed knowledge-based system

5.3 Evaluation of the narrative simulation construction system (NSCS)

Besides the KBS, the narrative simulation construction system (NSCS) is also evaluated. The KBS was further developed to accomplish and verify the proposed methodology by making use of the stored narratives of the presenting problems of clients. A snapshot of the system is shown in Figure 5.4. Workers store the narrative data into the knowledge base during their daily work. The unstructured narrative data is converted into a structured concept map for computer analysis. Then a narrative background is initiated based on the narrative prediction and construction algorithm. The decisions, intermediate narratives and endings are constructed by the HCBR and the SACM, respectively. Finally, a web interface of narrative simulation is generated for the learners to use. The detailed system interfaces is shown in Appendix G.
In the experiment, the mental health caring process for adolescents is selected as the topic. During the caring process, social worker interviews the client and carries out diagnostic assessment for evaluating client’s mental health status. The
worker is required to write a small narrative into the system to describe the problem of the client. Based on the presented problem, the 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. The quality of the cases is ensured by discussing the cases among the social workers of the organization in their weekly meeting. They are also reviewed periodically by the domain experts who are outside the organization. By filtering the incomplete cases that consist of missing data, 72 complete cases are used in the experiment. The cases are first analyzed by the FACM which converts the narratives into a structured data format. Secondly, the information of mental health assessment, development history, suicidal history, and family background is used and analyzed by the narrative prediction and construction algorithm, which constructs the beginning of the multi-linear narrative. Thirdly, treatment records and review records are used to deduce the decisions and intermediate narratives, which are analyzed by the HCBR and SACM algorithms. Finally, the termination records are used to check the ending of the output narratives. The output narrative has 6 levels, 40 narrative segments, and 39 decisions. The time taken to construct the narrative is about half an hour to one hour. The output narrative can be viewed through standard web browsers, so that users can access the narrative at any time and at any place where there is a computer.

The field test of the narrative simulation was conducted with a group of the case workers of the organization and social worker students who are studying mental health care. 17 participants were involved in the experiment. By adapting the narrative simulation evaluation proposed by McCrary et al. (1999), eleven questions
were set and they were rated from 1 to 5 (5 is highest agreement) on a Likert scale. The details of questionnaires can be found in Appendix H. 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 choosing the number (1) or (2), and neutral by choosing the number (3). The evaluation questions are categorized into different areas which include veracity, informative, cognitive, usability and affective. Table 5.1 summarizes the participant evaluations and includes 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 based on true stories, their perceptions on believing in the reality of the narrative were important. As a result, one feedback statement stated that the story was realistic, while another was concerned about the extent to which users can relate personally to the story. 41.2% indicated that they could relate personally, and 11.8% mentioned that they were unable to relate to it. 41.2% of participants said that the story was realistic, and 11.8% of them disagreed. 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. 29.4% believed they had learned something new, and 5.9% of them disagreed. 35.3% indicated that the exercise helped them to remember important things, and 35.3% of them disagreed.
Table 5.1: User evaluation results of the CNSS (n=17)

<table>
<thead>
<tr>
<th>Evaluation Questions</th>
<th>Design Category</th>
<th>Agree</th>
<th>Disagree</th>
<th>Neutral</th>
</tr>
</thead>
<tbody>
<tr>
<td>The exercise is realistic and authentic.</td>
<td>Veracity</td>
<td>41.2%</td>
<td>11.8%</td>
<td>47.1%</td>
</tr>
<tr>
<td>I can relate personally to the exercise.</td>
<td>Veracity</td>
<td>41.2%</td>
<td>11.8%</td>
<td>47.1%</td>
</tr>
<tr>
<td>The content is informative.</td>
<td>Informative</td>
<td>64.7%</td>
<td>11.8%</td>
<td>23.5%</td>
</tr>
<tr>
<td>I learned something new from the exercise.</td>
<td>Cognitive</td>
<td>29.4%</td>
<td>5.9%</td>
<td>64.7%</td>
</tr>
<tr>
<td>It helped me remember important things</td>
<td>Cognitive</td>
<td>35.3%</td>
<td>35.3%</td>
<td>29.4%</td>
</tr>
<tr>
<td>The length of exercise is appropriate.</td>
<td>Usability</td>
<td>70.6%</td>
<td>5.9%</td>
<td>23.5%</td>
</tr>
<tr>
<td>The exercise is easy to understand</td>
<td>Usability</td>
<td>64.7%</td>
<td>17.6%</td>
<td>17.6%</td>
</tr>
<tr>
<td>The questions are easy to answer</td>
<td>Usability</td>
<td>41.2%</td>
<td>35.3%</td>
<td>23.5%</td>
</tr>
<tr>
<td>The exercise is interesting</td>
<td>Affective</td>
<td>17.6%</td>
<td>23.5%</td>
<td>58.9%</td>
</tr>
<tr>
<td>The exercise made me feel uncomfortable</td>
<td>Affective</td>
<td>29.4%</td>
<td>52.9%</td>
<td>17.6%</td>
</tr>
<tr>
<td>Overall, the exercise is useful</td>
<td>Overall</td>
<td>23.5%</td>
<td>5.9%</td>
<td>70.6%</td>
</tr>
</tbody>
</table>

Three specific statements in the evaluation related to the usability of the simulation. Those were statements regarding the length of the simulation, the ease of understanding and the ease of answering the embedded questions throughout the exercise. 70.6% of users indicated that the length was appropriate. 64.7% of participants agree that the simulation was easy to understand. 41.2% of participants agreed that the questions were easy to answer with 35.3% disagreeing. Two statements were set to discover 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.

Another experiment was carried out to measure the learning outcome of the users. The participants were divided into two groups which include an experimental
group (8 participants) and a control group (5 participants), respectively. As shown in Figure 5.5, 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.

![Figure 5.5: Experimental group and control group of narrative simulation evaluation](image)

The training exercise was composed of 10 multiple choices questions. The questions were randomly selected from the cases of the knowledge base of the system, however, the cases used in the narrative simulation were excluded. The choices of questions, without the solutions, were generated based on CBR. The results of the evaluation are summarized in Table 5.2. It is interesting to note that 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.

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 from a series of qualitative and quantitative experiments.
Table 5.2: Results of learning outcome of the users

<table>
<thead>
<tr>
<th>Question</th>
<th>Averaged accuracy of control group</th>
<th>Averaged accuracy of experiment group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1</td>
<td>0%</td>
<td>25%</td>
</tr>
<tr>
<td>Q2</td>
<td>20%</td>
<td>25%</td>
</tr>
<tr>
<td>Q3</td>
<td>60%</td>
<td>87.5%</td>
</tr>
<tr>
<td>Q4</td>
<td>40%</td>
<td>87.5%</td>
</tr>
<tr>
<td>Q5</td>
<td>40%</td>
<td>37.5%</td>
</tr>
<tr>
<td>Q6</td>
<td>20%</td>
<td>25%</td>
</tr>
<tr>
<td>Q7</td>
<td>60%</td>
<td>25%</td>
</tr>
<tr>
<td>Q8</td>
<td>40%</td>
<td>50%</td>
</tr>
<tr>
<td>Q9</td>
<td>40%</td>
<td>62.5%</td>
</tr>
<tr>
<td>Q10</td>
<td>20%</td>
<td>87.5%</td>
</tr>
<tr>
<td>Q1 to Q10</td>
<td>34%</td>
<td>51.25%</td>
</tr>
</tbody>
</table>

5.4 Prerequisites and limitations of the case study

The social service organization is selected as the reference site based on the assumptions mentioned in Section 3.4. The selected reference site is an organization which the workers are willing to share their knowledge among each other. The organization consists of the required organizational atmosphere of promoting experimentation, and believes on the implementation of new idea, tolerating mistakes, sharing and encouraging learning. A workflow system has been built for the acquisition of the required narrative data and information from the knowledge workers. The quality of the data and information are ensured by the expertise inside the organization, and they are periodically reviewed by the domain experts outside the organization as well. The narrative information of the case study fulfils the required format which consists of beginning, decision and consequence, and they are clearly identified and retained in the knowledge repository.

There are three major limitations of the case study. Firstly, the CNS method can only deal with text-based narrative. Videos or sound records need to be converted
into text in order to adopt the CNS. Secondly, the CNS method collects and synthesizes the current practice of an organization. As a result, the knowledge workers may not learn new things that are outside of the organizational practice through the CNS. Thirdly, one of the most important objectives of CNS is to manage narrative knowledge in a more systemic manner. CNS is not suitable for industries or domains which consist of little narrative knowledge. Some well-defined problems which can be fully addressed by mathematical algorithms are not appropriate for CNS.

5.5 Summary

A case study and a controlled experiment were carried out at a social service organization in Hong Kong during the implementation of the CNSS. A survey was distributed for measuring the performance of the KBS of the CNSS. The results show that the users are satisfied with the KBS and they agree that the KBS can improve decision making and knowledge retrieval.

Another survey was distributed for measuring the usability of the narrative simulation construction system (NSCS). A narrative simulation was constructed on the basis of real cases from the organization. The field test of the narrative simulation was conducted with the workers of the company and social work students who study mental health care. The results indicate that the participants generally agree that the narrative is informative, realistic and authentic. The participants were able to relate personally to the narrative and they said they learnt something new from the narrative. They agree that the length of the narrative was appropriate, and the narrative was easy to understand and the questions about it were easy to answer.
The participants commented that on the whole the constructed narrative was useful.

A controlled experiment was also carried out for measuring the learning outcome created by the system. The results show that the average mark of the experimental group was 17% higher than that of the control group, which indicates that the system can improve their work. On the whole, the capability of the CNSS is successfully realized in the selected reference site and good results are obtained.
Organizational learning (OL) is the key to competitive advantage in the knowledge economy. A review of the archive literature reveals that the existing OL approaches do not fulfill the requirements needed for the important knowledge processes and OL facilitating factors. Traditional methods focus on providing abstract knowledge which is ineffective for gaining experience of the work. The methods of data collection and construction of narrative simulation are labor intensive, time consuming and costly. They are inadequate for coping with this fast moving world in which knowledge within organizations is changing rapidly.

There is a need for the establishment of a methodology, which enables knowledge creation, storage and retrieval, transfer and sharing, and application, as well as fulfilling the facilitating factors, for achieving OL. A bottom-up approach for the collection of narratives is much needed for saving the time and reducing the cost of keeping the knowledge updated. Text mining and concept mapping are required for converting the narrative knowledge into a structured format. Automatic narrative generation and AI technologies are incorporated to generate narrative simulation automatically, so that workers can learn and examine new ideas in simulations in a cost effective, time effective and labour effective manner. The generation of narrative requires that scenarios based on multiple narrative resources be constructed, in order to prevent and the direct use of previous narratives.

Based on the result of the literature review, a computational narrative simulation (CNS) methodology and hence a computational narrative simulation
system (CNSS) are presented which facilitate the automation of the processes of collection, prediction and construction of narratives. CNS attempts to overcome the limitations of traditional narrative simulation methods, which make use of previous narratives directly without any enhancement. The CNS automatically combines multiple narratives and constructs scenarios that have a high probability of occurring in the near future.

The CNSS contains four core algorithms which are: fuzzy associated concept mapping (FACM), a narrative prediction and construction algorithm, hybrid case-based reasoning (HCBR), and self-associated concept mapping (SACM). The FACM provides organizations with the ability to convert the inefficient unstructured textual documents into a structured format which can be processed easily by computer. The FACM extracts concept maps from natural language texts and suggests propositions for assisting knowledge workers to construct concept maps. Hence, the knowledge workers have extra time to re-think their written text and to look at their content knowledge from another angle, so as to increase their learning speed and improve the quality of their learning.

The HCBR has been developed so as to provide an accurate and high quality decision support function. It also allows the organizations to assimilate the valuable experience and knowledge of the workers. This helps to drive the continuous improvement of service quality in the organization. HCBR has been successfully applied for inferring the decision choices in narrative simulation. The transformation of multiple narrative data into narrative simulations has been computerized.
The SACM has been developed for enhancing the capabilities of knowledge elicitation, knowledge representation and knowledge inference. An elicitation algorithm has been developed for the automatic construction of the SACM from rational databases. An inference algorithm of the SACM which incorporates a Constrained Fuzzy Spreading Activation (CFSA) model is built for quantitative inference. The SACM has the advantages of simplicity, naturalness, higher laymen learning capability, smaller data size, and faster computational speed than traditional problem solving methods. It would be useful for simulating human learning activities. The narrative prediction and construction adopts a time-series forecasting method for automatically combining multiple narratives into a single narrative and for constructing scenarios that have a high probability of occurring in the near future. This enables workers to learn proactively.

A series of experiments have been conducted to quantitatively evaluate the performance of these algorithms. The results of the experiments show that the FACM can successfully convert the unstructured narrative text into a structured format that can be easily processed by computers. An average precision rate of over 87% for scientific abstracts, over 83% for technology news, and over 92% for a health care narrative database were achieved. In addition, an average recall rate of over 78% for scientific abstracts, over 74% for technology news, and over 90% for the health care narrative database was achieved. The results show that the FACM increases the recall rate (about 40% to 50% improvement) and maintains a high precision rate (over 80%) when compared with the baseline algorithm. The FACM algorithm successfully associates the text with the original propositions, which is promising for its use as the basic domain independent algorithm to extract
propositions. From the management perspective, the algorithm provides an interactive way for knowledge workers with extra time on their hands to re-think their concept maps, written texts and to look at their knowledge from another angle.

The verification of the narrative prediction and construction algorithm is based on a real case experiment. There is over 70% accuracy in the prediction of propositions when the time interval is set to 3 months or above. This means that the predicted proposition would very likely appear in the coming 3 months. The accuracy is good, even though the accuracy of the method is calculated on a basis on strict restrictions and strict conditions. The measurement of the performance of the HCBR is based on a real case experiment. The results are compared with well-known inference algorithms, i.e. CBR and RBR. It is interesting to note that the accuracy of CBR and RBR converges much slower than that of HCBR. In particular, HCBR has a higher accuracy than CBR when the number of learning cases is small. On the whole, the HCBR approach reaches an accuracy of over 80% with 40 learning cases, and it performs better than when CBR is applied by itself (about 12% to 22% improvement) or when RBR is applied by itself (about 3% to 47% improvement).

Two real case experiments have been carried out to evaluate the effectiveness of the SACM. Both of the experiments are compared with CBR. The first one deals with structured data. The results indicate that SACM has a higher correlation with the result of laymen of the domain. The second experiment deals with unstructured narrative data. The results show that the accuracy of SACM is higher than CBR when the number of learning cases is over 40. The accuracy of CBR converges at
The performance of the CNSS was evaluated as a whole through a case study and a controlled experiment which were carried out at a social service organization. A prototype CNSS was purpose built for the case management of the organization. A survey was distributed for measuring the performance of the knowledge-based system (KBS) of the CNSS. The results show that the users are satisfied with the KBS and they agree that the KBS can improve decision making and knowledge retrieval. Another survey was distributed for measuring the usability of the narrative simulation construction system (NSCS) of the CNSS. A narrative simulation was constructed on the basis of real cases from the organization. The results indicate that the participants generally agree that the narrative is informative, realistic and authentic. The participants were able to relate personally to the narrative and they said they learnt something new from the narrative. They agree that the length of the narrative was appropriate, and the narrative was easy to understand and the questions about it were easy to answer. They agreed that the exercise helped them to remember important things. The participants commented that on the whole the constructed narrative was useful. A controlled experiment was also carried out for measuring the learning outcome created by the system. The results show that the average mark of the experimental group was 17% higher than that of the control group, which indicates that the system can improve their work.

On the whole, the present study makes a number of contributions to the state of the art of OL. Firstly, a computational narrative simulation (CNS) methodology is established for enabling narrative simulation to be created at any time and in any
place. Next, a computational narrative simulation system (CNSS) is developed and built for the realization of the capability of the CNS methodology. Four core computational intelligent algorithms have been purpose built for supporting the development of the CNSS. These algorithms not only contribute significantly to the advancement of the computational intelligent technologies but also provide an important means for the development of the CNSS. People can try their actions out through the simulation system, which enables learning in a way that is cost effective, fast, appropriate, flexible, and ethical. The automatic transformation of multiple narrative data into a narrative simulation was possible, and achieved the desired design intentions. The application of narrative simulation increases the impact of the experience so that users are encouraged to rethink the decisions they make in their daily work. This is particularly important because most of the valuable new knowledge is formed during this process.

The CNSS integrates the knowledge processes into the existing organizational workflow. Workers represent their knowledge in concept maps and share it with others during their daily operations. Thus, organizational knowledge can be externalized, acquired, shared, reused, and replenished, all within the organization. This helps the organization to provide better learning for their staff and results in better application of existing knowledge. It facilitates knowledge creation, knowledge sharing, and knowledge replenishment as well as increasing organizational coherence. The workload of workers and the investments in knowledge management are minimized, and the parallel operation of knowledge management administration and the business processes is avoided. On the whole, the present study constitutes a significant step forward for OL.
Due to the complexity of organizational learning, a number of interesting areas for exploration could not be explored in the present study. Some suggestions for future work are provided in this Chapter. These suggestions include: applications in other industries; further enhancement of the capability of knowledge acquisition; individual and shared mental models; and multimedia integration.

7.1 Applications in other industries

In the present study, the narrative simulation is only implemented in a single case study at a social service organization. The system should be implemented in other social service organizations for testing. Interesting results may be found from integrating narratives from different organizations.

Since the CNSS is designed as a generic platform, the system can be applied to other organizations containing narrative knowledge. Further study should be carried out for possible implementation of the system in other industries such as in aircraft maintenance using narrative-like format for recording the flight maintenance elements, and in education sector using narratives for teaching and learning, etc. Hence, comparative analyses can be carried out within a single industry and among different industries.

7.2 Further enhancement of the capability of knowledge acquisition

Data reliability is the concern with the consistency of the data collected and the
repeatability of the data collection method; while data validity is the correctness and reasonableness of data. In the present study, a trade-off has been made between data reliability and validity. The validity is ensured by the expertise inside and outside the case study organization. Some measures of reliability are suggested for future work in order to ensure the reliability of the collected data. For example, Cronbach's alpha (Cronbach, 1951) is a common internal consistency measure.

Moreover, the CNS method collects and synthesizes the current practices of an organization. As a result, workers may not learn things that are outside of the organizational practice through the CNSS. It is suggested that web agent technologies be incorporated for searching for relevant information, which is beneficial to the organization from the internet or from selected websites.

Due to need to collect a massive amount of data, technologies of text summarization would be useful for abstracting and extracting useful information. The summarized information can be added as one of the resources for creating narrative simulation. This will enlarge the knowledge base and enhance the capability of knowledge acquisition of the system.

7.3 Individual and shared mental models

A mental model is a model of an individual’s thinking process about how something works in the real-world. Workers need to develop appropriate mental models so that they can follow the appropriate way to apply the information and knowledge for their work. A shared mental model represents the common beliefs, values and thinking of a group or an organization.
In the present study, the thinking of workers is represented in terms of narrative information. The FACM partly externalizes the workers’ individual mental models in terms of the concept mapping representation, and the FACM also represents a shared mental model as an aggregation of the individuals’ concept maps. It is suggested that the current study be integrated with computational organizational models that study and model individual and group behaviors so as to provide a deeper understanding of individual and shared mental models.

### 7.4 Multimedia integration

The present study is applied to text-based narratives. The integration of multimedia such as graphics, animation, and sound effects is needed. Text may be boring especially for young readers. It will be an interesting area to investigate the integration of visual and aural media along with written text. A number of researchers are currently developing models of vocal storytellers by coordinating text to a speech synthesizer. Thus, a truly interesting and engaging experience for readers would be created.

Moreover, the system is still not fully automatic and needs the simulation designer to intervene. Interactive real-time questioning and answering narrative will be the next step of the system. A multi-agents system should be incorporated in which computational intelligent agents can act as characters or actors in a narrative in which they are able to interact with each other. Readers could then act as characters in the narrative and interact with the computational agents so that the narrative changes through readers’ intervention.
REFERENCES


References


References


References


Carley, K.M. (2002b) Computational organizational science and organizational engineering, Simulation Modelling Practice and Theory, 10, 253-269


References


References


References


Hopcroft, J.E.; and Ullman, J.D. (1979) Introduction to automata theory, languages, and computation, Addison-Wesley: Reading, MA


References


References


McCrary, N.; and Mazur, J.M. (1999) Evaluating Narrative Simulation as Instructional Design for Potential To Impact Bias and Discrimination, Proceedings of Selected Research and Development Papers Presented at the National Convention of the Association for Educational Communications and Technology [AECT] (21st, Houston, TX, February 10-14, 1999); see IR 019 753.


References


Poole, D.; Mackworth, A.; and Goebel, R. (1998), Computational Intelligence: A Logical Approach, Oxford University Press


<table>
<thead>
<tr>
<th>Reference</th>
</tr>
</thead>
</table>
References


References


References


PUBLICATIONS

Refereed Journal Articles:


Conference Presentations and Publications:


1. cc: Coordinating conjunction
2. cd: Cardinal number
3. det: Determiner
4. ex: Existential there
5. fw: Foreign word
6. in: Preposition or subordinating conjunction
7. jj: Adjective
8. jjr: Adjective, comparative
9. jjs: Adjective, superlative
10. ls: List item marker
11. md: Modal
12. nn: Noun, singular or mass
13. nns: Noun, plural
14. nnp: Proper noun, singular
15. nnps: Proper noun, plural
16. pdt: Predeterminer
17. pos: Possessive ending
18. prp: Personal pronoun
19. prp$: Possessive pronoun
20. rb: Adverb
21. rbr: Adverb, comparative
22. rbs: Adverb, superlative
23. rp: Particle
24. sym: Symbol
25. to: to
26. uh: Interjection
27. vb: Verb, base form
28. vbd: Verb, past tense
29. vbg: Verb, gerund or present participle
30. vbn: Verb, past participle
31. vbp: Verb, non-3rd person singular present
32. vbz: Verb, 3rd person singular present
33. wst: Wh-determiner
34. wp: Wh-pronoun
35. wp$: Possessive wh-pronoun
36. wrb: Wh-adverb
1. IF the POS of a word is <vb> AND <rb> Then the POS of the word is changed to <vb>
2. IF the POS of a word is <jj> AND <nn> Then the POS of the word is changed to <nn>
3. IF the first word of the sentence is <vp> THEN np: <vb><nn>
4. IF the POS of a word contains <nn> AND the word before it is <det> THEN the POS of the word is changed to <nn>
5. IF the POS of a word contains <jj> AND the word before it is <det> THEN the POS of the word is changed to <jj>
6. IF the POS of a word contains <jj> AND the word before it is <det> THEN the POS of the word is changed to <jj>
7. IF the POS of a word contains <nn> AND the word before it is <jj> THEN the POS of the word is changed to <nn>
8. IF the POS of a word contains <nn> AND the word before it is <prp$> THEN the POS of the word is changed to <nn>
9. IF the POS of a word contains <jj> AND the word before it is <prp$> THEN the POS of the word is changed to <jj>
10. IF the POS of a word contains <vb> AND the word before it is <prp> THEN the POS of the word is changed to <vb>
11. IF the POS of a word contains <rb> AND the word before it is <prp> THEN the POS of the word is changed to <rb>
12. IF the POS of a word contains <to> AND the word after it is <vb> THEN the POS of the word is changed to <rb>
13. IF the POS of a word contains <in> AND the word after it is <vb> THEN the POS of the word is changed to <rb>
14. IF the POS of a word contains <vb> AND the word after it is <det> THEN the POS of the word is changed to <vb>
15. IF the sentences contains NO <nn> THEN the POS of first word’s POS contains <nn> is <nn>
16. IF the sentences contains NO <nn> THEN the POS of first word’s POS contains <vb> is <nn>
## Appendix C – Concept Acquisition Case Set

### APPENDIX C – CONCEPT ACQUISITION CASE SET

<table>
<thead>
<tr>
<th>Problem</th>
<th>Solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;&lt;cc&gt;&lt;vb&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;</td>
<td>7,8,9;7,11,12</td>
</tr>
<tr>
<td>&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;</td>
<td>2,3,4;2,3,6;8,9,10+11+12</td>
</tr>
<tr>
<td>&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;</td>
<td>2,3,4;6,7,8;10,11,12</td>
</tr>
<tr>
<td>&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;</td>
<td>2,3,4;2,6,7;9,12,13;11,12,13</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>1,10,11;3,10,11;5,10,11;7,10,11;9,10,11</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>1,8,9;3,8,9;5,8,9;7,8,9</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>1,6,7;3,6,7;5,6,7</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>1,4+5+6+7+8,9;3,4+5+6+7+8,9</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>1,4,5;3,4,5</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>3,4,5;3,4,7</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>1,3,4+5+6;1,7,8</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>4,7,8;6,7,8;12,13,14</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>1,2,3;1,2,5;1,2,7;1,2,9;1,2,11</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>1,2,3;1,2,5;1,7,8+9+10</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>1,2,3;1,2,5;1,7,8;10,11,12</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>1,2,3;5,6,7;9,10,11</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>1,2,3;1,9,10;1,9,12;1,9,14</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>1,2,3;1,5,6;1,5,8;1,5,10;1,5,12;1,5,14</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>1,2,3+4+5</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>1,2,3;3,4,5;3,4,7;3,4,9</td>
</tr>
<tr>
<td>&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;cc&gt;&lt;nn&gt;&lt;vb&gt;&lt;nn&gt;</td>
<td>4,5,6+1+2;4,5,8+1+2</td>
</tr>
</tbody>
</table>
APPENDIX D – NEWS ARTICLES’ LINKS

iPhone spurs Web traffic, if not music sales
By Reuters, January 19, 2008, 1:18 PM PST

Jihadi software promises secure Web contacts
By Reuters, January 19, 2008, 1:54 PM PST

U.S. venture funding up nearly 11 percent in 2007
By Dawn Kawamoto, January 19, 2008 12:23 AM PST

Credit issuer says data lost for 650,000 customers
By Reuters, January 18, 2008, 4:59 PM PST

SEC urged not to revive ‘terrorist’ watch list
By Reuters, January 18, 2008, 3:26 PM PST

Week in review: Apple goes into thin ‘Air’
By Steven Musil, January 18, 2008, 10:00 AM PST

Feds appeal loss in PGP compelled-passphrase case
By Declan McCullagh, January 18, 2008 1:58 PM PST

NASA considering making a virtual world
By Daniel Terdiman, January 18, 2008 1:16 PM PST

OnOne acquires novel image-resizing software
By Stephen Shankland, January 18, 2008 1:27 PM PST

Turner, NBA extend relationship to digital
By Reuters, January 18, 2008, 5:04 AM PST
APPENDIX E – USER INTERFACE OF CASE LIBRARY

Figure E1: Login screen of the case library

Figure E2: Case list of the case library
Appendix E – User Interface of Case Library

Figure E3: Case forms of the case library

Figure E4: Case record of the case library
Appendix E – User Interface of Case Library

Figure E5: Intake form of the case library

Figure E6: Decision support of the case library
Appendix E – User Interface of Case Library

Figure E7: Unstructured data conversion of the case library

Figure E8: Fuzzy Associated Concept Mapping Tool
Appendix E – User Interface of Case Library

Figure E9: Records of converted concept maps

Figure E10: An example of converting a text into a concept map
Appendix E – User Interface of Case Library

**Figure E11:** Editing a concept in the Fuzzy Associated Concept Mapping Tool

**Figure E12:** Editing a relationship in the Fuzzy Associated Concept Mapping Tool
Appendix E – User Interface of Case Library

Figure E13: Personalization setting in the Fuzzy Associated Concept Mapping Tool
(a)

Figure E14: Personalization setting in the Fuzzy Associated Concept Mapping Tool
(b)
Figure E15: Selection of different type of knowledge in the Fuzzy Associated Concept Mapping Tool
APPENDIX F – CASE LIBRARY EVALUATION

QUESTIONNAIRE

Case Library Evaluation Questionnaire

For the purpose of continuous improvement of the design of the case library, we would be grateful if you could spend a few minutes to complete this questionnaire. The information you provided would only for the above purpose, so it is highly confidential.

Date

<table>
<thead>
<tr>
<th>Personal Information</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Name:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Position:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Department:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Part I. Overall System

<table>
<thead>
<tr>
<th>Operation of the Case Library</th>
<th>Strongly Agree</th>
<th>Agree</th>
<th>Neutral</th>
<th>Disagree</th>
<th>Strongly disagree</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Ease of Learn</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decision support function</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reporting function</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data input</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Information retrieval</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>System maintenance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| 2 Ease of use                 |                |       |         |          |                  |
| Decision support function    |                |       |         |          |                  |
| Reporting function           |                |       |         |          |                  |
| Data input                   |                |       |         |          |                  |
| Information retrieval        |                |       |         |          |                  |
| System maintenance           |                |       |         |          |                  |

| 3 It is easy to install (if applicable) |                |       |         |          |                  |
|                                     |                |       |         |          |                  |

| 4 It is easy to implement (if applicable) |                |       |         |          |                  |
|                                        |                |       |         |          |                  |

Content of the Case Library

<table>
<thead>
<tr>
<th>5 Is the content correct (e.g. forms, format, wordings, etc)? If no, please specify any</th>
<th>No</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>Yes</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
6  Is the content enough? If no, what items are suggested to be added? Please specify.

7  Is there any redundant content? If yes, please specify:

8  Is the content easy to understand? If no, please specify:
### Others

<p>| | | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>9</td>
<td>The system can assist caseworker to make decision in shorter period of time than before</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>The process of case management is improved by using this system</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>The system can improve the efficiency of casework's work</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>I prefer to use the new system rather than the old method</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Any suggestion for further improvement on this system? Please specify:

---

### Part II. Functional Features

#### Decision Support Function

<p>| | | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>The function is useful</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>The suggestion is useful</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>It can improve the efficiency of the old process</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>It can bring convenience to the user</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Any suggestion for further improvement on this function? Please specify:

---
### Reporting Function

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>The function is useful</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>It can improve the efficiency of the old process</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>It can bring convenience to the user</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Any suggestion for further improvement on this function? Please specify:


### Data Input

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>The function is useful</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>It can improve the efficiency of the old process</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>It can bring convenience to the user</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Any suggestion for further improvement on this function? Please specify:


Figure G1: Records in narrative simulation construction

Figure G2: Editing a new narrative simulation
Appendix G – User Interface of Narrative Simulation

Figure G3: Selecting the parameters for creating a new narrative simulation

Figure G4: The generation of background of a new narrative simulation
Figure G5: The generation of decisions under the background

Figure G6: The generation of narrative under a decision
Appendix G – User Interface of Narrative Simulation

Figure G7: The generation of narratives and decisions for completing the whole narrative simulation

Figure G8: The interface for parameter setting of time-series forecasting
Appendix G – User Interface of Narrative Simulation

Figure G9: The interface for setting of the case base of the Hybrid Case-based Reasoning

Figure G10: The interface for setting of the rule base of the Hybrid Case-based Reasoning
Appendix G – User Interface of Narrative Simulation

Figure G11: The interface for setting of the cases of the Self Associated Concept Mapping

Figure G12: The interface of learners of using the narrative simulation
Narrative Simulation Evaluation Questionnaire

For the purpose of continuous improvement of the design of the narrative simulation, we would be grateful if you could spend a few minutes to complete this questionnaire. The information you provided would only for the above purpose, so it is highly confidential.

Date

<table>
<thead>
<tr>
<th></th>
<th>Strongly Agree (1)</th>
<th>Agree (2)</th>
<th>Neutral (3)</th>
<th>Disagree (4)</th>
<th>Strongly Disagree (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>The exercise is realistic and authentic</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
<tr>
<td>2</td>
<td>I can relate personally to the exercise</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
<tr>
<td>3</td>
<td>The content is informative</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
<tr>
<td>4</td>
<td>I learned something new from the exercise</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
<tr>
<td>5</td>
<td>It helped me remember important things</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
<tr>
<td>6</td>
<td>The length of exercise is appropriate</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
<tr>
<td>7</td>
<td>The exercise is easy to understand</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
<tr>
<td>8</td>
<td>The questions are easy to answer</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
<tr>
<td>9</td>
<td>The exercise is interesting</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
<tr>
<td>10</td>
<td>The exercise made me feel uncomfortable</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
<tr>
<td>11</td>
<td>Overall, the exercise is useful</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
</tbody>
</table>

Any suggestion for further improvement on this system? Please specify:

______________________________________________________________________________
______________________________________________________________________________
______________________________________________________________________________
______________________________________________________________________________
APPENDIX I – SOURCE CODE OF NARRATIVE SIMULATION

The computational narrative simulation system is built based on Microsoft Active Server Page and Microsoft Visual Basic 6.0. The major modules of the system include the FACM module, the HCBA module, the SACM module, the prediction module, and the narrative construction modules. The source code of the modules is included in the provided CD. In particular, the FACM module consists of Mod_CMap.bas, Mod_POS.bas, Frm_Map.frm, Frm_Thesaurus.frm, Frm_EditConcept.frm, and Frm_EditLink.frm. The HCBA module consists of Frm_HCBA_CB.frm, Frm_HCBA_RB.frm, and Mod_HCBA.bas. The SACM module consists of Frm_SACM.frm, Frm_SACMGraph.frm, and Mod_SACM.bas. The prediction module consists of Frm_Forecast.frm, Frm_IniNarrative.frm, and Mod_Prediction.bas. The narrative construction module consists of Frm_Narrative.frm, Frm_NarrativeDB.frm, and Mod_DB.bas.