A Quantitative Modeling Analysis Method of Mental Models Combined with Link Tables

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Abstract: As the basic structure of human cognition, mental models manifest the structure of people's cognition, experience and knowledge of the real world. Most of the existing studies focus on the structure and content of mental models, and a more objective and comprehensive approach to modeling mental models has not been proposed. To address this issue, firstly, the unstructured text data is transformed into a structured link matrix from link relationship representation for further computational work. A page ranking algorithm is also introduced to identify the important nodes of the mental model network to achieve key intent capture and design concept transformation. After that, a content network-based clustering analysis is used to identify the evolutionary process of users' mental activities. Finally, a case study analysis is utilized to verify the effectiveness of this modeling and analysis method, which provides a reference for future theoretical research and application practice in related fields.

Keywords: user mental model, multidimensional modeling, link table

1 INTRODUCTION

To deeply explore user needs, researchers are committed to analyzing human psychological processes through mental model theory(Li, 2020)[8], revealing the nature of cognition and decision-making. The term mental model was first coined by Craik, it is one of the many assumptions, biases and impressions that have been established in people's minds about how they perceive the world, face new things and how act, and is also usually translated as mind models, thinking models or psychology models, etc(Craik, 1943)[3]. in existing studies in China. As human's understanding and view of the real world are constantly changing, the mental model will also continue to be influenced by the user's habits of thought(Wang, 2022)[11]. Although mental models originated from Burke's mental paradigm, they have also been commonly used in human interactions. Norman first identified three mental models of interactive systems from a systems perspective: the performance model, the thinking model, and the implementation model(Norman, 2017)[10].

From the current state of research at home and abroad, the theory of mental models can be widely applied in various types of information systems, mainly in key functions such as system user browsing, search tasks, and evaluation systems. In Zhang's study, the cognitive

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mechanisms and expressions of users in the process of information retrieval have been further explored and comprehensively analyzed(Zhang, 2008)[13]. After comprehensively considering the user's cognitive characteristics and integrating them with the user's cognitive factors, a user cognitive scenario that can present differentiation to the user is finally established by Borgman, thus promoting learning and collaboration among different users in the digital library information search process(Borgman, 2005)[1]. While Kim focused more on interpersonal cognition, he paid close attention to using different task scenarios during his experiments, and through the analysis of these elements, he found some factors that have a direct effect on user searches, such as emotion, cognitive style, and experience(Kim, 2001)[6]. In China, Han experimented with the influence of learning and mental models of users on the database Internet, and there have also been special studies on the optimization of shared mental models and mental model-based products in the group, hoping to improve users' experience(Han, 2017)[5]. Secondly, Zhang utilized mental models to study the mechanism of product category retrieval on e-commerce platforms and used techniques such as idea mapping to obtain the perception process of consumers' product category retrieval and the mechanism of the influence of mental models, and to reveal the mechanism of the difference between consumers' mental models and the expression model of product category retrieval(Zhang, 2014)[12].

From the above research, it can be seen that the current research on mental models by experts and scholars at home and abroad mostly focuses on the structure and content of mental models, but there is a lack of research on the fine-grained level of meaning, and a multi-dimensional modeling and analysis method of mental models with universal significance has not been developed. This article intends to integrate the theories and techniques related to complex networks and chain-link structures, to conduct in-depth research on the content, structure and activity trajectory of the model, and to realize the quantitative, analytical and structural model that can fully reflect the user's behavior.

2 MODEL EXPRESSION

The structured and quantitative analysis of the mental model requires the integration of the content, process, and associations of thinking activities to form a multidimensional model that integrates reasoning, expression, and analysis. This article proposes to use techniques such as data matrix, process linkage, content network, and key node identification to quantitatively analyze the data in the cognitive process to discover the convergence patterns of user thinking in the cognitive process and analyze the complexity and evolutionary pathways of the cognitive process.

2.1 Data Matrix Expression

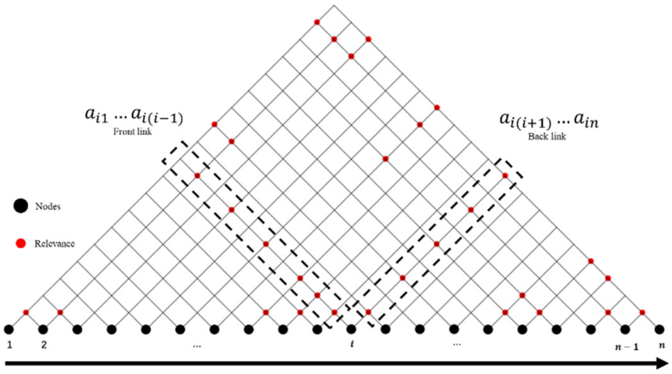

Figure 1: Link table.

After pre-processing, the thinking nodes extracted from the cognitive corpus are used to construct a structured node-association link matrix(Goldschmidt, 2011)[4]. This matrix fundamentally stores the underlying linkage data of the nodes so that interconversion between unstructured linguistic data and structured data can be achieved, and the nodes are encoded according to the relevance of the cognitive concepts, and if the relevance between the nodes is high, then they are noted as relevant, and conversely, if the relevance is low, then they can be ignored and are non-relevant. Based on the segmentation of the design nodes, the nodes are determined and coded for inter-concept correlation to form a connection matrix from Figure 1. If it is an arbitrary node i named as N_i, then the link vector corresponding to it can be encoded as 0 or 1 depending on whether the node is in correlation with other nodes.

$$L_i = (l_{i1}, l_{i2}, \ldots, l_{in}) \quad (1)$$

In the above equation, the L_i is the link vector of the N_i. l_{in} are the series of associated code values between N_i and N_n. At the end of coding, each node gets a link vector of length the number of overall nodes, and a complete link vector table is obtained by merging the link vectors of all nodes in the operation. In addition, it is a meaningless operation whether a node is associated with itself or not, so the self-linkage of all nodes is uniformly set to zero.

2.2 Process Link Modeling

The difficulty in the study of mental models stems from the fact that the process of human mental activity is ambiguous, variable and uncertain. Therefore, this paper uses a feature vector-based ranking method to determine the importance of mental nodes based on the use of link tables to identify users' mental nodes, i.e., the PageRank algorithm to calculate the PR value of each node to capture the fluctuations and transitions of mental activity.

In 1998, Larry Page and Sergey Brin of Stanford University proposed the core idea of the PageRank algorithm, which was based on a common method for judging the importance of academic papers: if a web page is linked to many other web pages, it is more important. If a web page with a high PR value links to another web page, the PR value of the linked web page will increase accordingly(Brin and Page, 1998)[2]. The PR value represents the probability of a web page being visited and is generally denoted as $1/N$ and N is the total number of web pages. Therefore, the sum of the PR values of all web pages is generally 1.

In general, the PR values of the nodes in the network are calculated as follows:

$$PR(pi) = \sum_{pj \in M_{pi}} \frac{PR(pj)}{L(pj)} + \frac{1-a}{N} \qquad (2)$$

In this formula, M_{pi} refers to the set of nodes in this network out of the chain to pi the set of all nodes in this network, $L(pj)$ refers to the number of outgoing links of node pj to other nodes, N refers to the number of all nodes in this network, and a is usually taken as 0.85 (a is expressed as the probability of node i linking to a random node). The final PR value needs to be obtained after continuous iterative operations when the PR value after the operation is smoothed.

2.3 Content Network Analysis

The content network is an expression of the link network model, which is a way to describe the concept evolution process in the design process through the form of a network, i.e., the network linking relationship between concepts. Compared with the chain table method, the concept linking method focuses more on exploring the inference and development barriers of concept points from the network characteristics and tries to discover more hidden information from the spatial association between concepts, to enrich the expression of concept points.

The content network breaks the constraint of classifying the same thinking activity based on time series only, and its formation process is mainly based on the results of cluster analysis(Liao, 2016)[7]. The clustering of content nodes of the same type together to form a cluster of nodes is known as clustering. The connections between nodes do not change as a result of clustering, but only the deeper the node cluster, the more node clusters are formed, and the more thought content is represented. Along with the emergence of thematic clustering, a complete thought pattern emerges. In the specific operation process, the CONCOR algorithm is used(Ma, 2012)[9]. Cluster analysis was performed.

The purpose of the CONCOR clustering algorithm is to find design-relevant features in the design process and to analyze and process them for clustering families. the CONCOR transformation is the core of this classification method. Constructing the matrix $A = (a_{ij})_{n \times m}$, then:

$$b_{ij} = \frac{\sum_{k=1}^{m}(a_{ik} - \overline{\delta_i})(a_{jk} - \overline{\delta_j})}{\sqrt{\sum_{k=1}^{m}(a_{ik} - \overline{\sigma_i})^2}\sqrt{\sum_{k=1}^{m}(a_{jk} - \overline{\sigma_j})^2}} \qquad (3)$$

In this equation, $\overline{\delta}$ is the row average of A . And the matrix $B = (b_{ij})_{n \times n}$ is called the CONCOR transform of A and is denoted as $B = CONCOR(A)$, where b is called the CONCOR transform coefficient.

3 CASE STUDIES

3.1 Experimental Data Processing

This experiment is based on the design of online novel data visualization. To objectively and comprehensively obtain users' needs and improve the accuracy, objectivity and comprehensiveness of the experiment, an anonymous questionnaire was distributed online to collect data. The questionnaire consists of two parts: the first part is to collect basic information from users, including personal information and web novel reading; the second part is the core part of the questionnaire, which guides users' cognition and informs them to think out of the box and describe the experience of using the web novel app and users' needs as much as possible.

In Table 1, the survey questionnaire was distributed for 1 month, the distribution method was online, and the target users were online novel forum users. A total of 103 questionnaires were received, of which 96 were valid, with a return rate of 93.2%. The Cronbach a coefficient was 0.904 calculated by SPSS, indicating that the questionnaire results are reliable.

The results of the questionnaire results need to be pre-processed by manual recognition of the data before proceeding to mental model modeling. The specific process is: 1.The text data is cleaned, irrelevant content is deleted, and duplicate content is removed. 2. Screening key concepts from the overall text data. 3. Determine the linking relationship between key concept nodes based on relevance. After pre-processing, a total of 82 sentences of usable text were obtained in Table 2.

Table 1: Questionnaire results statistics table.

Statistical quantities		**Data**	Percentage（%）
Gender	Male	57	59.38
	Female	39	40.62
Education	High School and below	41	42.71
	Specialty and Undergraduate	44	45.83
	Master and above	11	11.46
Age	Under 18	14	14.58
	18~30	47	48.86
	Over 30	35	36.46
Average reading years	1 year and below	7	7.29
	2~3 years	14	14.59
	4~5 years	13	13.54
	More than 5 years	62	64.58

Table 2: Data summary table.

Nodes	**Text data**	Node Concepts	Link Nodes
1	You can find a lot of good novels in the library, and you can enter the library for reference when you don't know what to read	Book Library	2 4 5 14 18 51 52 71 75 82
…			…

41	The list of "Characters" and the "Collection of settings (worldview, characters, and events)", and the ability to like individual characters.	Enhanced reading immersion	7 10 13 14 18 22 23 44 46 54 61 62 72 78 79 81
…			…
82	Batch management for easy deletion, moving and downloading	Book Batch Management	18 42 46

3.2 Cognitive Convergence Analysis

Referring to the overall distribution of the link table, all the nodes in the grid are arranged in the horizontal and vertical axes according to the numbering order, and the nodes of the two axes correspond to each other in turn. With the diagonal line as the division, the whole grid is divided into the front link area at the bottom left of the diagonal line, which is called the F area, and the area labeled B area at the top right of the diagonal line is the back-link area. If there is a link relationship between two nodes, i.e., the link matrix is represented by a "1", it is marked with a blue square in the grid diagram and the opposite is reflected as blank. At the same time, the change in link length can also map the transformation of users' thinking in a certain sense. The link points closer to the diagonal are called short links, which reflect the sudden change and activeness of thinking; the long nodes far from the diagonal show the precipitation and stability of thinking.

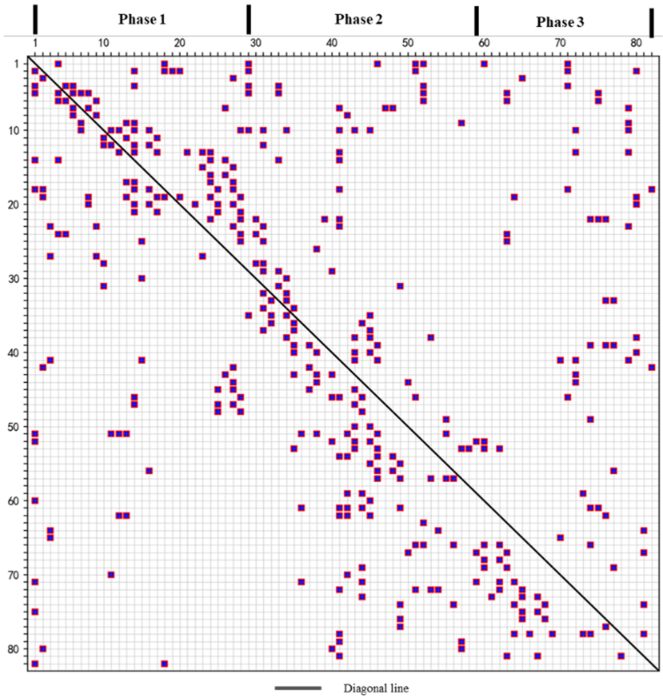

Figure 2: Overall distribution of the link chart.

As shown in Figure 2, the user's mental activity process can be roughly decomposed into three stages according to the distribution of node links. Nodes $N_1 \sim N_{29}$ are the unfolding stage of thinking, in which there are more short links between nodes than long links, which indicates that thinking is more active and novel in this stage. However, later in this stage, the number of long links exceeds the number of short links, reflecting the local convergence of thinking activity.$\mathrm{N}_{30}\sim\mathrm{N}_{59}$ $N_{30} \sim N_{59}$ are intermediate links of thinking, whose link characteristics are more convergent compared to the previous link, and some nodes show long links associated with the previous link. The stage of $N_{60} \sim N_{82}$ is the end of thinking, and this stage has a significant increase in long links relative to the previous stage, indicating that the thinking activity at this stage is more mature and stable.

3.3 Content Network Clustering

Cluster analysis spans the time interval and splits the overall thought process into different categories to explore the development process of the concept. The node size is adjusted according to the PR value after doing continuous linear function mapping, and then the description of the nodes is transformed into vectors using the Roberta model and then clustered using the CONCOR algorithm, and the final clustering results are shown in Figure 3, with different colors representing different categories. In other words, Table 3 shows the clustering of the demands and their specific percentages.

Table 3: Clustering results table.

Usage requirements	**Usage Preferences**	**Link nodes**	**Quantities**
Social requirements	Welfare Factors	17,29,64,65,67	5 (6.10%)
	Reading and sharing	49,50,62,63,66,74,78	7 (8.54%)
	Kudos for evaluation	22,39,40,54,59,73,76,77	8 (9.76%)
Functional requirements	Simplify operations	8,13,26,36,47,48,57,70,82	9 (10.98%)
	Additional Functions	10,11,12,23,28,31,34,35,42,43,44,45,72,81	14 (17.07%)
	Search Categories	4,5,6,51,52,71,75	7 (8.54%)
Reading requirements	Book Recommendation	14,24,32,33,56,61,80	7 (8.54%)
	Interface design	1,2,3,7,9,16,18,19,20,21,27,37,41,46,58,60,68,69,79	19 (23.17%)
	Advertising fees	15,25,30,38,53,55	6 (7.32%)

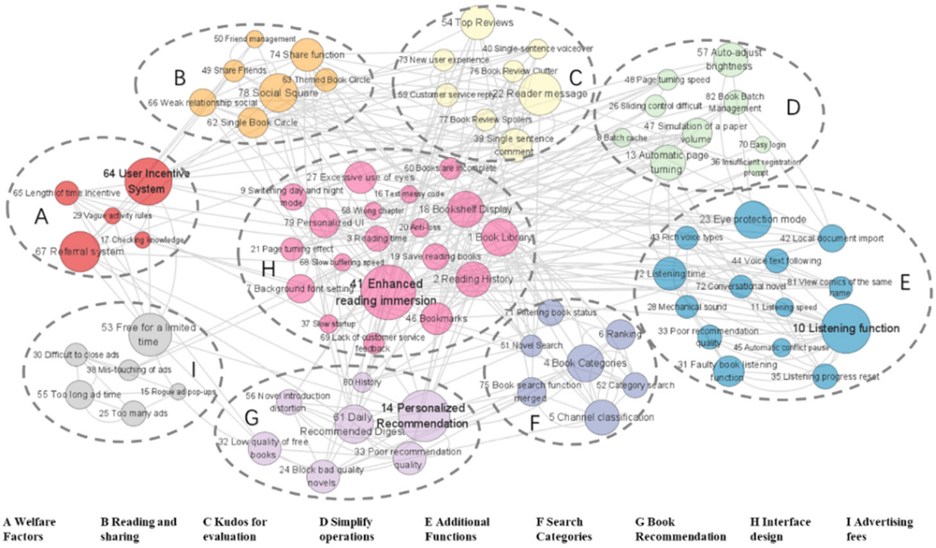

Figure 3: Content network clustering graph.

3.4 Critical Node Identification

After performing the clustering analysis of the content network, it is necessary to combine the PR values to achieve the analysis of the importance of each node in the user's thought process. In Figure 4, the fluctuation of node PR values is shown. As shown in the figure, the PR value has relatively large ups and downs in the initial stage. There are three nodes(N_{15}, N_{17} and N_{29}) that have the smallest PR value of 0.002 in this phase; while the node with the largest PR value is N_{14} This indicates that in the first stage, users' thinking is relatively active and their thought activities are in a messy situation. Compared with the first stage, excluding the N_{41}, the node PR value in the second stage is significantly lower and the fluctuation is more stable, indicating that the user's thinking process tends to be stable after a period of activity. After the third stage of the thinking process, the PR value is still low compared with the first stage, but the fluctuation range has increased, indicating that the user's thinking tends to converge and mature, and new concepts are still produced at the end of the thinking process. Take the highest PR value N_{41} The node with the highest PR value, for example, has both pre-linked and post-linked features, and belongs to a stage with greater design cognitive complexity, which indicates that it not only takes over and relates to the concepts already generated, but also has the effect of inspiring and guiding the output of subsequent concepts.

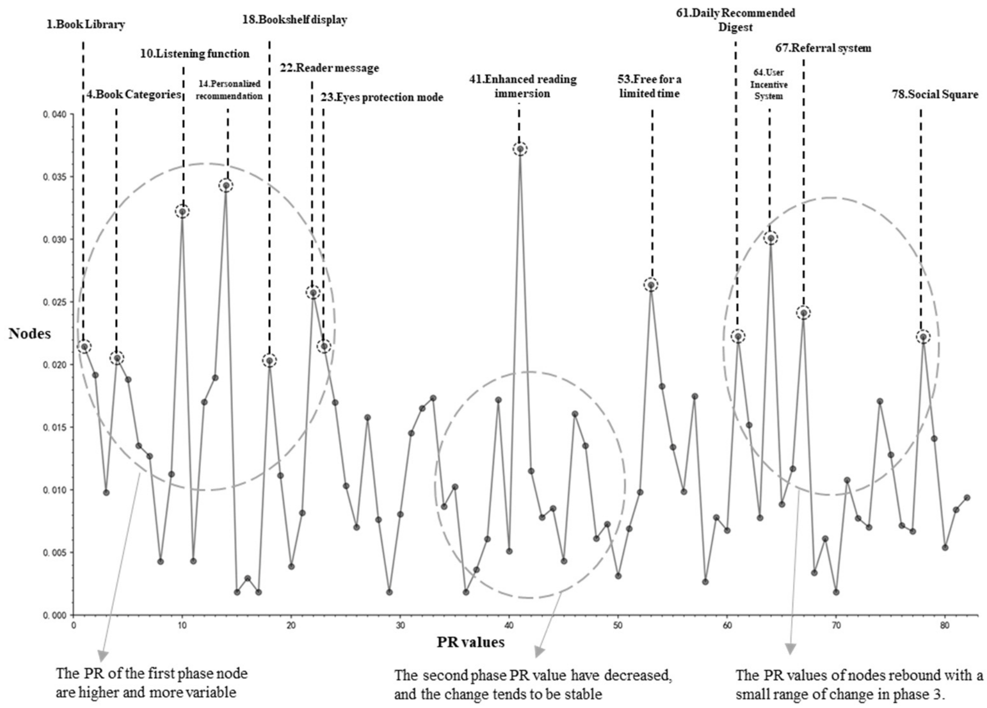

Figure 4: Node PR value analysis chart.

Reviewing the text data, the N_{41} summarizes the user's reading demand for the online novel APP, i.e., the most basic demand, and if that demand is not satisfied, the user is highly likely to give up using the APP. N_{64} introduces the operation mode of reading APP, but the follow-up fails to deepen the study, so its PR value is relatively high in the local area, but not so significant overall. N_{10} and N_{14} $\mathbf{N_{14}}$ arse the concept nodes of "listening function" and "personalized recommendation" respectively, which are also the extreme points of PR value fluctuation within the local area. Although their no-front link is a new concept point, it plays a role in promoting the generation of subsequent concepts and shows the evolutionary trend of local innovation.

4 CONCLUSIONS

In this paper, we split and reorganize the text data based on questionnaires to transform discrete unstructured text data into computable structured data. These data are built into a data matrix, followed by process linking and forming a content network, and finally generating a multidimensional mental model. The relationship between different nodes in the user mental activity process is explored from the perspectives of temporality, correlation and spatial distribution relationship, and the complex characteristics of the mental activity process are transformed into assessable quantitative indicators to propose a universal user mind analysis idea, which provides a reference direction for design theory and application practice in related fields. However, the limited distribution time of the questionnaire makes the number of respondents constrained, so the questionnaire results are not strong enough to characterize the overall audience of online novels. In the follow-up study, the mechanisms that influence users' cognitive systems, such as geographical differences and users' cultural levels, should also be considered, to improve the accuracy and universality of users' mental models and further enrich the connotation and extension of mental model research theories.

REFERENCES

[1] Borgman C L, Smart L J, Millwood K A, et al. (2005). Comparing Faculty Information Seeking in Teaching and Research: Implications for the Design of Digital Libraries. J. Journal of the Association for Information Science & Technology, 56(6):636–657.

[2] Brin S, Page L. (1998). The Anatomy of a Large-Scale Hypertextual Web Search Engine. J. Computer Networks and ISDN Systems, 30(1-7):107-117.

[3] Craik K W. (1943). The Nature of Explanation. M. Cambridge UK: Cambridge University Press, 51-54.

[4] Goldschmidt G, Sever A. (2011). Inspiring Design Ideas with Texts J. Design studies,32(2).

[5] Han Z B. (2017). The Driving Factors for the Evolution of Users' Mental Model of Academic Database Based on Distributed Cognition. J. Journal of the China Society for Scientific and Technical Information, 36(1):79-88.

[6] Kim K S. (2001). Information-seeking on the Web. J. Library & Information Science Research, 23(3):233-255.

[7] Liao X, Li Z H, Xi Y J. (2016). Modeling and Analysis of Users' Knowledge Network in Innovative Community Based on Clustering. J. Computer Simulation, 0(4):316-319.

[8] Li J X. (2020). the Visual Thinking of User Interaction Experience in UI Design. J. Science and Technology Innovation Herald, 17(14):250-252.

[9] Ma Y, Zhang X D, Shen J H. (2012). Study on Fixed-points of CONCOR Clustering. J. Chinese Journal of Engineering Mathematics, 29(04):620-624.

[10] Norman A D. (2017). Emotional Design. J. Industrial Design, 0(6):32-33.

[11] Wang Y. (2022). A Review of Mental Models in Interface Design. J. Desing, 35(13):89-92.

[12] Zhang J J, Xue C X, Gan L R. (2014). Study on the Measurement of Mental Models Based on the Hierarchical Concept:A Test in Web Search of Commodity Category. J. Journal of the China Society for Scientific and Technical Information, 33(6):644-658.

[13] Zhang Y. (2008). the Influence of Mental Models on Undergraduate Students' Searching Behavior on the Web. J. Information PRocessing & Management, 44(3):1330-1345.