

## PAPER

# A Cognitive Load Theory-Based Approach to Integrating Mobile Fragmented Learning Resources

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## ABSTRACT

With the rapid development of mobile internet technology, mobile fragmented learning has become a mainstream learning mode due to its convenience and flexibility. However, the vast quantity of learning resources available online often varies in quality and lacks coherent organization, leading to excessive cognitive load and reduced learning efficiency. Existing research primarily focuses on resource integration based on content similarity clustering or user behavior data, while largely overlooking learners' cognitive characteristics and the dynamic regulation of cognitive load. As a result, current integration methods fail to meet the cognitive needs of fragmented learning. To address this issue, this study proposes a resource integration framework for mobile fragmented learning grounded in cognitive load theory. On one hand, it constructs a cognitively aligned resource analysis model using design structure matrix (DSM) to rank and categorize cognitive load elements in learning materials. On the other hand, it applies DSM-based decoupling and clustering strategies to decompose resources into manageable cognitive units and support personalized aggregation. This dual approach aims to reduce intrinsic cognitive load and enhance the efficiency of resource organization. The findings offer a cognition-informed pathway for mobile learning resource design and hold significant implications for optimizing fragmented learning experiences and advancing mobile learning theory and practice.

## KEYWORDS

cognitive load theory, mobile fragmented learning, resource integration, design structure matrix (DSM), cognitive load management

## 1 INTRODUCTION

With the rapid development of mobile internet technology, the popularity of mobile devices such as smartphones and tablets has greatly increased, and people's learning methods have undergone significant changes. Mobile fragmented learning has gradually become one of the mainstream learning modes [1–4]. This learning mode has the characteristics of convenience and flexibility [5, 6],

Hu, L., Liu, D. (2025). A Cognitive Load Theory-Based Approach to Integrating Mobile Fragmented Learning Resources. *International Journal of Interactive Mobile Technologies (IJIM)*, 19(16), pp. 60–76. <https://doi.org/10.3991/ijim.v19i16.57605>

Article submitted 2025-04-08. Revision uploaded 2025-06-27. Final acceptance 2025-07-04.

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allowing learners to acquire knowledge during fragmented time. However, the current mobile fragmented learning resources are large in quantity and growing rapidly [7, 8], but generally suffer from problems such as uneven quality, disorganized structure, and lack of systematization [9]. When facing massive fragmented learning resources, learners often need to spend a lot of time and effort to filter, integrate, and understand information [10], which undoubtedly increases learners' cognitive load, resulting in low learning efficiency and difficulty in achieving effective knowledge construction and capability improvement. Therefore, how to integrate mobile fragmented learning resources, reduce learners' cognitive load, and improve learning outcomes has become an important problem to be solved urgently.

At present, many scholars have conducted research on the integration of mobile fragmented learning resources [11–14]. For example, some studies adopt clustering methods based on content similarity to integrate fragmented learning resources. Literature [15], for instance, analyzes features such as text content and multimedia elements of resources, grouping similar resources into one category to improve the organization of resources. However, this method only focuses on the external features of resources and ignores learners' cognitive characteristics and cognitive load changes during the learning process, resulting in integrated resources that may not match learners' cognitive levels and learning needs, making it difficult to effectively reduce learners' cognitive load. Some other studies are based on user behavior data. For example, literature [16] integrates learning resources by analyzing learners' behavior data such as click counts and browsing time. Although this considers part of learners' needs, it mainly relies on historical behavior data and cannot reflect learners' current cognitive state and changes in learning context in real time, so the integration effect has certain limitations. In addition, most existing studies lack in-depth application of cognitive load theory [17–20] and have not fully considered the reasonable distribution and regulation of cognitive load in the fragmented learning process, resulting in integration methods that are not ideal in reducing cognitive load and improving learning efficiency.

The main research content of this paper includes two parts. The first part is the analysis of mobile fragmented learning resources based on cognitive load theory, specifically including DSM-based sorting and DSM-based hierarchical division. DSM-based sorting analyzes and ranks the cognitive load elements of mobile fragmented learning resources to clarify the degree of influence of different resources on learners' cognitive load, providing a basis for resource integration. DSM-based hierarchical division classifies mobile fragmented learning resources according to the hierarchical structure of cognitive load, constructing a hierarchically clear resource system so that learners can choose appropriate learning resources according to their own cognitive levels and learning needs. The second part is the optimization of mobile fragmented learning resource integration based on cognitive load theory, including DSM-based decoupling and DSM-based clustering. DSM-based decoupling decomposes complex learning resources into relatively independent cognitive units, reducing the interaction between cognitive elements and lowering learners' intrinsic cognitive load. DSM-based clustering aggregates resources with similar cognitive load characteristics into different categories according to the cognitive load characteristics of resources and learners' cognitive needs, forming personalized learning resource packages, improving the efficiency of resource integration and the targeting of learning.

## 2 ANALYSIS OF MOBILE FRAGMENTED LEARNING RESOURCES BASED ON COGNITIVE LOAD THEORY

### 2.1 DSM-based sorting

In the mobile fragmented learning scenario, learners face a large number of discrete knowledge units. These units form a complex cognitive dependency network due to differences in content association, logical order, and other factors. The resource analysis approach based on DSM sorting deconstructs these dependency relationships to provide a basis for the rational regulation of cognitive load. Specifically, first, mobile fragmented learning resources are converted into nodes in the DSM, where directed edges between nodes represent cognitive dependency relationships of resource content, constructing a design structure matrix that reflects the cognitive logic between resources. By calculating the total tasks of each column in the matrix, “top-level resources” without dependencies and “bottom-level resources” with high dependencies are identified. According to DSM sorting rules, top-level resources are placed in priority positions. These resources, as the “starting units” of cognitive load, have low dependency themselves and require little prerequisite knowledge, allowing learners to complete basic construction under a low cognitive load state; bottom-level resources serve as subsequent deepening content, whose gradually emerging dependency relationships comply with the “progressive knowledge construction” requirement in cognitive load theory, avoiding intrinsic cognitive load spikes caused by information overload.

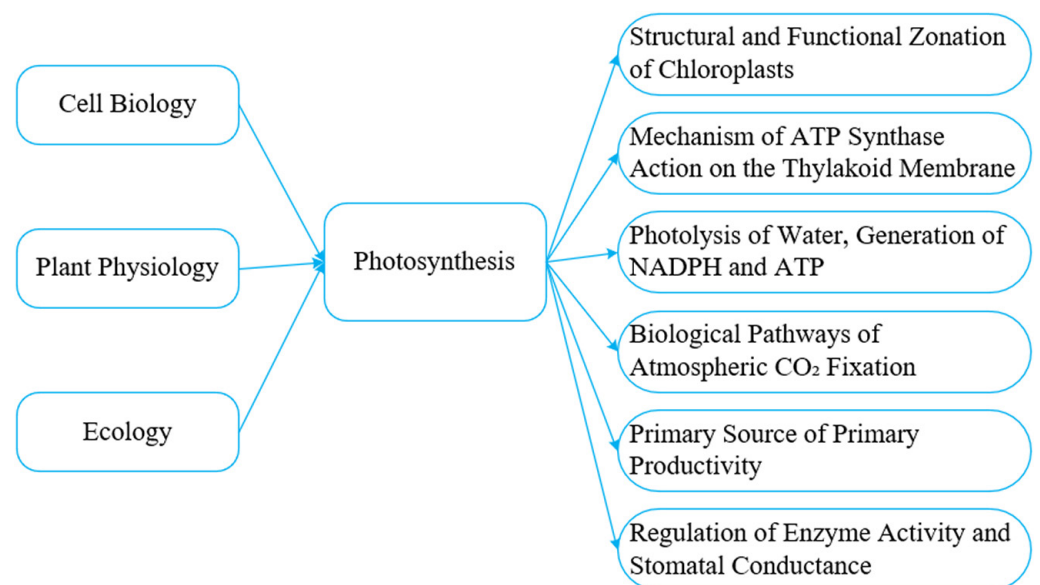


Fig. 1. Example of element dependencies in DSM sorting

The analysis approach based on DSM sorting can be further combined with the “intrinsic cognitive load” and “extraneous cognitive load” regulation goals in cognitive load theory to form a hierarchical cognitive path of resources. The resource sequence obtained through sorting essentially makes explicit the interaction of cognitive elements: top-level resources, as foundational nodes of the knowledge graph, correspond to the “low intrinsic load phase” in cognitive load theory during their learning process. They are suitable for priority acquisition during fragmented

time, helping learners establish knowledge anchors; as the sequence moves downward, resource dependency relationships strengthen, and corresponding intrinsic cognitive load gradually increases. However, since DSM sorting has reduced interference from irrelevant information by sorting dependency relationships, learners can integrate knowledge progressively under a clear logical context. Figure 1 illustrates an example of element dependencies during DSM sorting. The detailed calculation process is as follows:

Step 1. Start: calculate the total of each column's tasks

$$\text{Let: } m = \sum_{k=1}^v x_{uk}$$

$$U = 1, 2, \dots, v$$

$$V = \{1, 2, \dots, v\}$$

$$l = 1$$

Step 2. Find the columns whose sum is zero corresponding to tasks

Find  $j \in V$  such that  $U_j = 0$ , if there is no such task, then stop.

$$\text{Let: } RA(j) = l$$

$$l = l + 1$$

$$V = V - j$$

If  $V = \emptyset$ , then stop, calculation completed

Step 3. Calculate the remaining tasks

$$\text{Let: } I_i = I_i - a_{ki}, i \in N$$

Repeat Step 2.

## 2.2 DSM-based hierarchical division

In the analysis of mobile fragmented learning resources, the DSM-based hierarchical division method constructs a cognitive dependency network among resources, transforming the complex knowledge system into a structure that can be hierarchically parsed, thus supporting gradient management of cognitive load. Specifically, each fragmented learning resource is first abstracted as a node in the DSM, and directed connections between nodes represent the cognitive reachability relationships among resources—that is, whether understanding one resource requires another resource as a prerequisite. By defining the reachable set  $E(O_u)$  and the predecessor set  $X(O_u)$ , “source nodes” without prerequisite dependencies and “terminal nodes” without subsequent reachability can be identified. According to DSM hierarchical division rules, source nodes are first divided into the highest level because they can be learned independently without prerequisite knowledge, corresponding to the “low intrinsic cognitive load” basic units in cognitive load theory; then, the divided nodes are removed, and new source nodes are iteratively searched in the remaining network to form middle and bottom levels, making the resource hierarchy intuitively reflect the complexity of cognitive dependencies and providing learners with clear cognitive path guidance.

The iterative process of DSM hierarchical division essentially explicitly deconstructs the hierarchy of cognitive load. The highest-level source nodes, since  $E(O_u)$  contains only themselves and nodes at the same level, do not need to handle complex prerequisite dependencies during learning, allowing learning to start with the lowest extraneous cognitive load, which conforms to the core principle of cognitive load theory to “reduce irrelevant cognitive load”; middle-level nodes have an expanding intersection of  $X(O_u)$  and  $E(O_u)$ , meaning they need to integrate knowledge from multiple prerequisite resources, corresponding to moderate intrinsic cognitive load, suitable for gradual introduction after learners build a basic cognitive framework;

bottom-level terminal nodes'  $X(O_u)$  contains multiple layers of prerequisite nodes and require integrating a complex knowledge network, forming high-level cognitive load. This hierarchical mechanism enables learners to choose appropriate-level resources according to their own cognitive state and degree of time fragmentation, avoiding cognitive overload caused by direct contact with high-load content. The top-level nodes in the multi-level structure cannot be accessed by higher-level nodes, and the intersection of  $X(O_u)$  and  $E(O_u)$  equals  $E(O_u)$ , i.e.:

$$E(O_u) = E(O_u) \cap X(O_u) \quad (1)$$

Representing the levels from top to bottom as  $M_1, M_2, \dots, M_m$ , where 1 is the level number, the hierarchical division  $\prod_1(O)$  can be written as:

$$\prod_1(O) = [M_1, M_2, \dots, M_m] \quad (2)$$

Assuming the reachable set and predecessor set of the subgraph composed of nodes in  $O-M_0-M_1-\dots-M_{j-1}-M_j$  are denoted by  $E_{k-m}(O_u)$  and  $X_{k-m}(O_u)$ , respectively. The node set in the  $j$ -th layer in forward hierarchical division is denoted by  $DM_j$ , and the node set in the  $j$ -th layer in backward hierarchical division is denoted by  $YM_j$ , with empty sets denoted by  $DM_0$  and  $YM_0$ . If the 0-level is defined as the empty level, the iterative algorithm for hierarchical division  $\prod_1(O)$  is  $YM_j = \{u \in (V-YM_0-YM_1-\dots-YM_{j-1}) \mid E_{j-m}(O_u) \cap X_{j-m}(O_u) = E_{j-m}(O_u)\}$ . This iterative algorithm can be used as a criterion to identify terminal nodes or new terminal nodes. Similarly, the criterion for identifying source nodes is  $DM_j = \{u \in (V-DM_0-DM_1-\dots-DM_{j-1}) \mid E_{j-m}(O_u) \cap X_{j-m}(O_u) = X_{j-m}(O_u)\}$ .

The hierarchical knowledge graph structure obtained by DSM hierarchical division can be further assigned hierarchical attributes to each resource unit through automated labeling methods. Without changing the original topological relationships, this constructs a resource analysis framework with both structural clarity and flexibility. Cognitive load theory emphasizes the effective use of "germane cognitive load," that is, guiding learners to focus cognitive resources on constructing deep understanding through reasonable knowledge organization. Based on hierarchical labels, designers can design differentiated resource combinations for different learning goals: low-level resources are suitable for basic cognitive construction in fragmented scenarios, reducing extraneous load; middle-and high-level resources can form "micro-learning paths" through orderly concatenation, controlling intrinsic load while gradually increasing germane cognitive load to promote systematic knowledge integration.

### 3 INTEGRATION AND OPTIMIZATION OF MOBILE FRAGMENTED LEARNING RESOURCES COMBINED WITH COGNITIVE LOAD THEORY

#### 3.1 DSM-based decoupling

In the integration and optimization of mobile fragmented learning resources, the DSM-based decoupling method deconstructs the dependency relationships of complex cognitive units, transforming high interaction load knowledge modules into low-coupling independent units, thereby achieving effective control of intrinsic cognitive load. Specifically, fragmented learning resources are first mapped to a DSM matrix, whose elements represent the cognitive dependency relationships

between resources. The first step of decoupling is to identify independent resources without dependencies by screening empty rows and columns; these resources can be directly presented as basic units with priority. Their learning process does not involve handling complex interactions, corresponding to the “low intrinsic load” starting point in cognitive load theory, which helps learners establish knowledge anchors with minimal cognitive cost. For the remaining coupled blocks, the reachable matrix is calculated to locate strongly connected subsets, and the tearing operation selects key nodes with “minimal information input and maximal output” as decoupling breakthroughs.

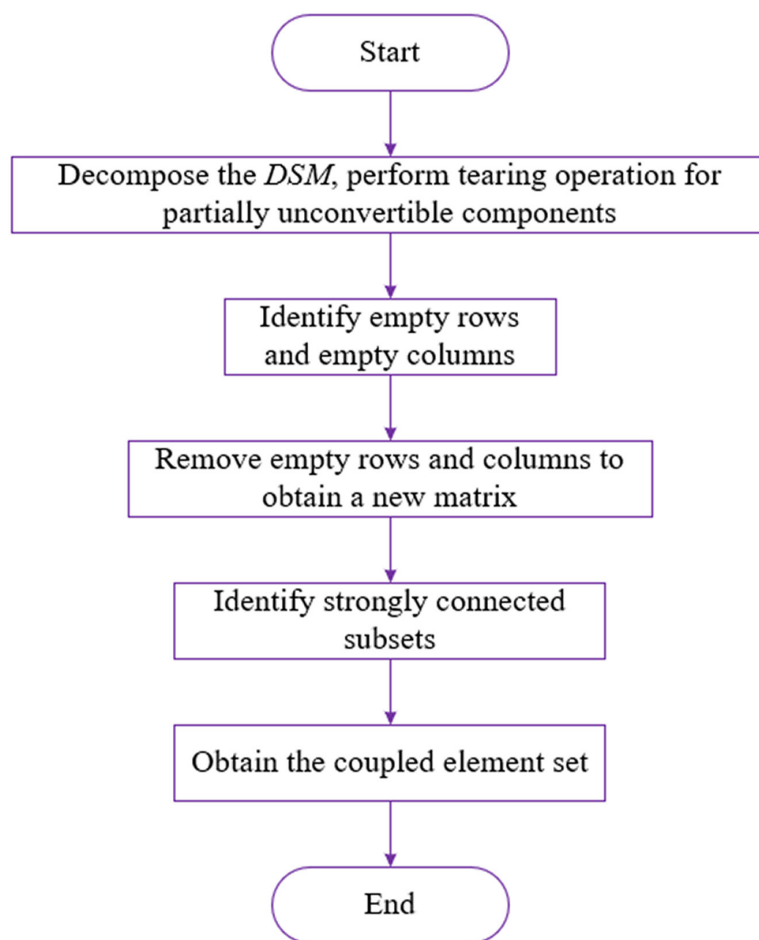


Fig. 2. DSM decoupling algorithm process

In traditional fragmented learning, unordered dependency relationships between resources increase learners’ extra load of screening and associating information. The decoupling process transforms the DSM matrix into a lower triangular structure, making the resource presentation sequence conform to the cognitive logic of “from no dependency to low dependency, from simple interaction to complex interaction”: the head independent resources act as “zero-load start units,” suitable for quick acquisition in very short fragmented time; the middle decoupled units control the number of interacting cognitive elements per learning session, keeping extraneous cognitive load within working memory capacity thresholds; the tail terminal resources integrate and apply knowledge formed in earlier decoupling stages. At this point, learners possess sufficient

cognitive schemas and can handle higher-order content with relatively low additional load. This integration and optimization strategy not only realizes granular decomposition of complex knowledge systems but also, through efficient iteration of the decoupling algorithm, enables learners to effectively construct knowledge in fragmented scenarios at minimal cognitive cost, fundamentally solving the overload problem caused by resource coupling in traditional integration methods. Figure 2 illustrates the workflow of the DSM decoupling algorithm. The algorithm process is as follows:

- Let  $Y$  be a subset of tasks within an iterative loop task
- Step 1. Set  $v = 1$
  - Step 2. Calculate  $O_u = YU_u / YP_u, u \in Y$
  - Step 3. Find the minimum  $O_j$
  - Step 4. Assign execution sequence number  $v$  to task  $j$
- Let  $Y = Y - j$ . If  $Y = \emptyset$ , execute step 5.
- $$YU_u = YU_u - x_{uj}, u \in Y$$
- $$YP_k = YP_k - x_{jk}, k \in Y$$
- $$v = v + 1$$
- Step 5. Check if there exists  $j \in Y$  such that  $YP_j = 0$ . If yes, reorder to generate a new execution sequence; if no, return to step 1.
  - Step 6. After decoupling all elements above the diagonal, terminate the process.

### 3.2 DSM-based clustering

Although explicit topological relationships have been established when constructing mobile fragmented learning resources, a large number of indirect associations still need deep mining. This paper chooses to introduce a DSM clustering method, which identifies “strong interaction clusters” with high-frequency interactions between resources, aggregating them into cognitively coherent units with high internal association and low external coupling. This allows learners to process resources within one cluster without frequently crossing different logical systems to call upon knowledge, directly reducing extraneous cognitive load caused by information dispersion. From the perspective of cognitive load theory, resources within the same cluster share similar cognitive schemas, and their aggregation process essentially converts scattered knowledge into “cognitive chunks,” conforming to the human working memory limit of processing  $4 \pm 1$  information units, thereby improving the utilization efficiency of germane cognitive load. Learners can focus their limited cognitive resources on deep integration of knowledge within clusters rather than expending them on disordered cross-cluster associations.

The specific steps for DSM clustering of mobile fragmented learning resources are as follows: First, identify independent resource units. These resources have no dependency relationships, and their learning process does not require invoking other knowledge. They can be presented as “zero-load start modules” with priority, helping learners accumulate basic knowledge points at minimal cognitive cost during fragmented time, avoiding startup barriers caused by complex dependencies; second, determine the core bus resources. These resources have strong associations with most other units and need to be placed at the central position of the clustering hierarchy as anchors of the cognitive framework. However, because they themselves bear high-load cognitive integration functions, they should be gradually introduced after learners have certain foundations to prevent early

cognitive overload; for the remaining resources, strong linked elements are iteratively searched to aggregate high-frequency interaction knowledge units into cognitive chunks with high internal coupling and low external coupling, so that each cluster forms a relatively complete micro-knowledge system, conforming to the working memory's processing limit of  $4 \pm 1$  chunks and reducing extraneous load caused by cross-cluster information switching; subsequently, weak links are connected to clusters in a lightweight manner to avoid irrelevant associations interfering with core cognitive paths; finally, based on cognitive load evaluation criteria, the best clustering scheme is selected to ensure that the intrinsic cognitive load of each cluster unit matches the time capacity of fragmented learning scenarios and learners' cognitive levels.

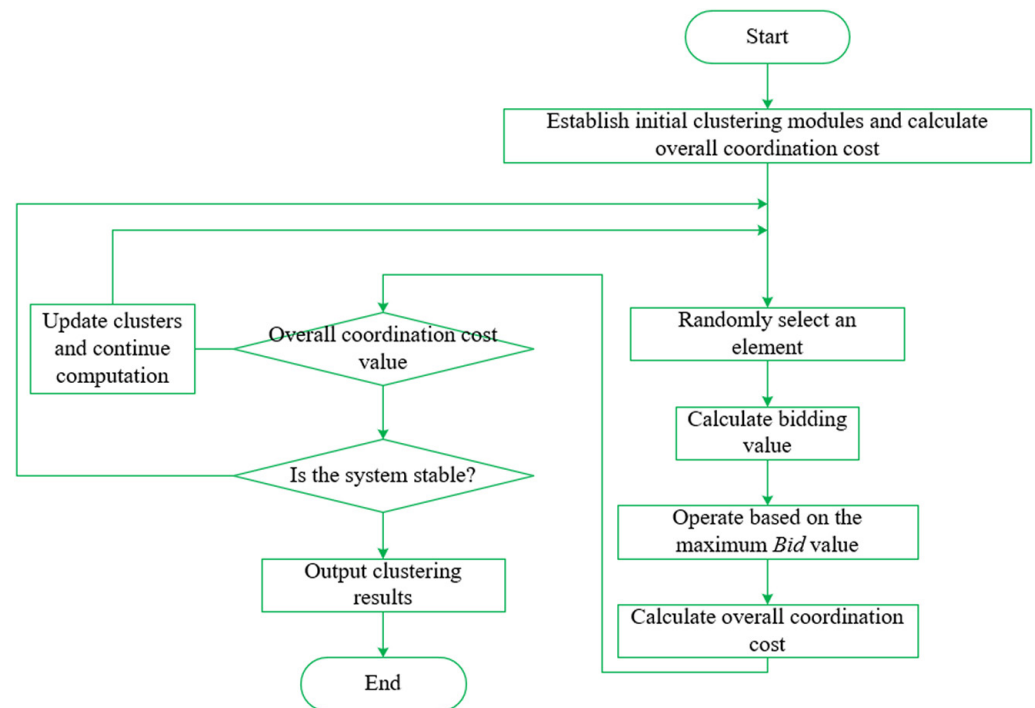


Fig. 3. DSM clustering algorithm process

There are many ways of DSM clustering. This paper chooses to use the function search method (FSM). FSM defines the total coordination cost in mobile interactions as the objective function. This cost essentially reflects the cognitive loss of learners when switching across resources, while the “bids” of each cluster correspond to the coordination cost reduction gains that may result from resource aggregation. The algorithm iteratively migrates resource units to the cluster with the highest bid, and if the total coordination cost significantly decreases, the clustering adjustment is confirmed. This process simulates the core mechanism of “reducing extraneous load by chunking” in cognitive load theory: within a highly cohesive resource cluster, a tight cognitive logic chain is formed, so learners do not need to frequently jump between low-related resources, focusing limited cognitive resources on deep integration of knowledge within the cluster. In addition, the algorithm introduces a second-highest bid to simulate a “simulated annealing” process, moderately accepting suboptimal solutions to avoid local optima, ensuring that clustering results cover diverse cognitive paths and preventing intrinsic cognitive load concentration caused

by over-pursuit of a single optimal solution. Ultimately, FSM dynamically balances strong intra-cluster associations with low inter-cluster interactions, constructing a “low coordination cost–high cognitive efficiency” resource aggregation model suitable for fragmented learning scenarios, providing quantitative support and optimization paths for precise cognitive load regulation at the algorithmic level. Figure 3 presents the workflow of the DSM clustering algorithm. Assume the dimension of the design structure matrix is denoted by  $l$ , the Boolean value in the design structure matrix is denoted by  $FTL(k,u)$ , the number of clusters is denoted by  $z$ , the number of elements in the design structure matrix is denoted by  $z_{SI}(j)$ , and the parameter controlling penalty type is denoted by  $POW_{zz}$ . The total interaction cost expression is given by:

$$TCC = \sum_{u=1}^l CC(TA_u) \quad (3)$$

Where,

$$COST(TASK_u) = \begin{cases} \sum_{k=1}^l [DSM(u,k) + DSM(k,u)] \\ \times \sum_{j=1}^z z_{SI}(j)^{POW_{zz}}, u \in j \cap k \in j \\ \sum_{k=1}^l [DSM(u,k) + DSM(k,u)] \\ \times SI^{POW_{zz}}, u \notin j \cup k \notin j \end{cases} \quad (4)$$

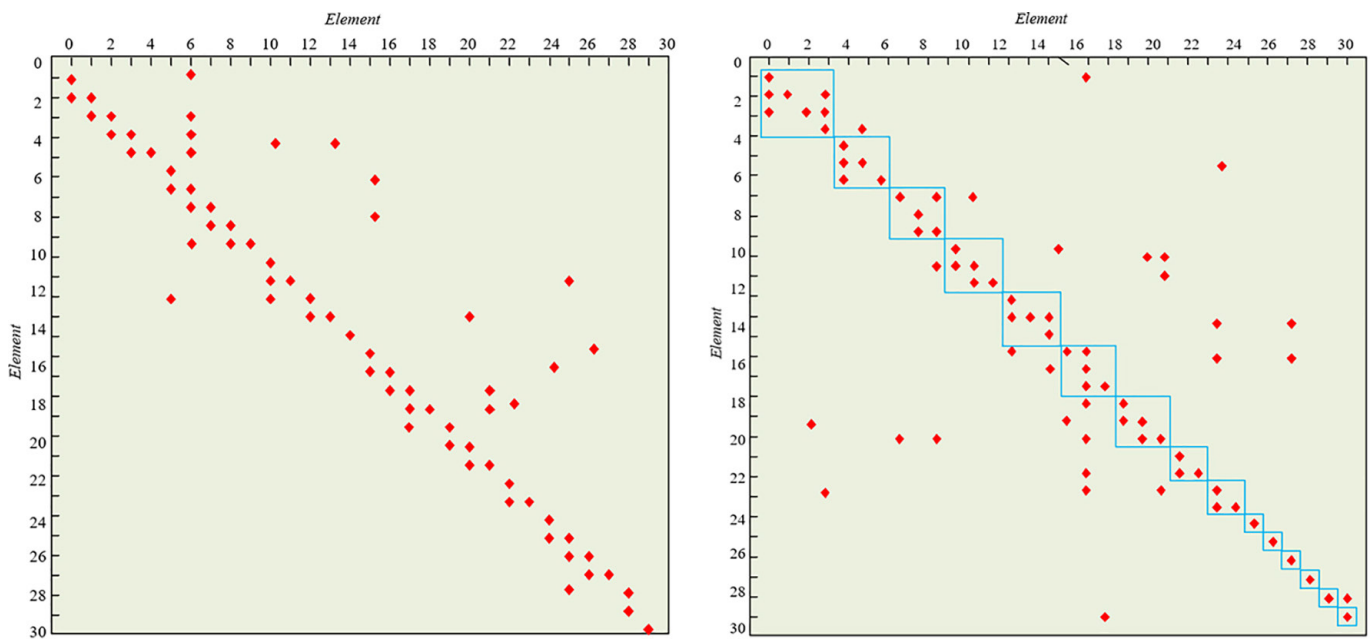
Assume the bid for cluster  $j$  targeting activity  $s$  is denoted by  $BID(CL_j, TA_j)$ ,  $POW_{BID}$  assigns importance to weak and strong interactions. The bid value of  $POW_{BID}$  depends on the cluster size, and the 0–1 variable  $X_{LXS}(j,k)$  indicates whether activity  $k$  is an element of cluster  $j$  (1 if yes). The bid of each cluster can be obtained by the following formula:

$$BID(CL_j, TA_j) = \sum_{k=1}^v \frac{[DSM(s,k) + DSM(k,s)]^{POW_{BID}}}{z_{SI}(j)^{POW_{BID}}} \times X_{LXS}(j,k) \quad (5)$$

## 4 EXPERIMENTAL RESULTS AND ANALYSIS

Figure 4 shows the scatter plot of the mobile fragmented learning resource structure matrix and the DSM clustering results. The scatter plot on the left side of Figure 4 presents the initial distribution of the mobile fragmented learning resource structure matrix. The red dots are scattered in the two-dimensional space without obvious clustering features, reflecting the disorder of cognitive dependency relationships among resources. This disorder causes learners to handle a large number of cross-unit association retrievals when accessing resources, increasing extraneous cognitive load. The DSM clustering results on the right side divide multiple resource clusters with blue boxes. The red dots within each cluster are highly concentrated, indicating that the algorithm successfully identified strongly associated cognitive units, forming cohesive resource chunks. The cluster in the upper left corresponds to “basic concepts and simple applications,” the cluster in the lower right corresponds to “complex cases and comprehensive practice,” and the clusters in the middle are layered according to cognitive difficulty gradients, constructing

a load progression path from low to high. Figure 4 intuitively shows the structural integration effect of DSM clustering on mobile fragmented learning resources. Both experimental data and theoretical analysis jointly prove that the method proposed in this paper significantly improves resource utilization efficiency and cognitive load regulation ability by mining cognitive associations and optimizing resource chunks, providing a scientific and effective solution for resource integration in mobile fragmented learning.



**Fig. 4.** Scatter plot of mobile fragmented learning resource structure matrix and DSM clustering results

The convergence curve in Figure 5 clearly shows the cost reduction process of the DSM clustering algorithm when optimizing the integration of mobile fragmented learning resources. The vertical axis “Cost” quantifies the cognitive coordination cost in resource interaction, and the horizontal axis “Epoch” is the number of iterations. The curve shows a steep decline at the initial stage, with cost quickly dropping from about 2500 to 1300, indicating that the algorithm efficiently identified strongly associated resources and aggregated them into low-interaction clusters, greatly reducing cross-cluster cognitive loss. Between 50 and 100 epochs, cost stabilizes briefly and then continues to decline, reflecting the simulated annealing mechanism that avoids local optima and ensures clustering covers diversified cognitive paths. Finally, it stabilizes and converges near 1200, with cost reduced by 52% compared to the initial value, proving that the algorithm achieves a global optimum through iteration, making the cognitive coordination cost after resource integration stable within the low-load range manageable by working memory. The convergence curve in Figure 5 not only verifies the computational efficiency of the DSM clustering algorithm but also visually presents the effectiveness of the method in cognitive load regulation by quantifying the cost reduction. Experimental data and theoretical analysis jointly demonstrate that this method significantly reduces the cognitive coordination cost of learning resources by iterative optimization of resource clustering, achieving the goal of “controllable load and efficient learning” in mobile fragmented learning.

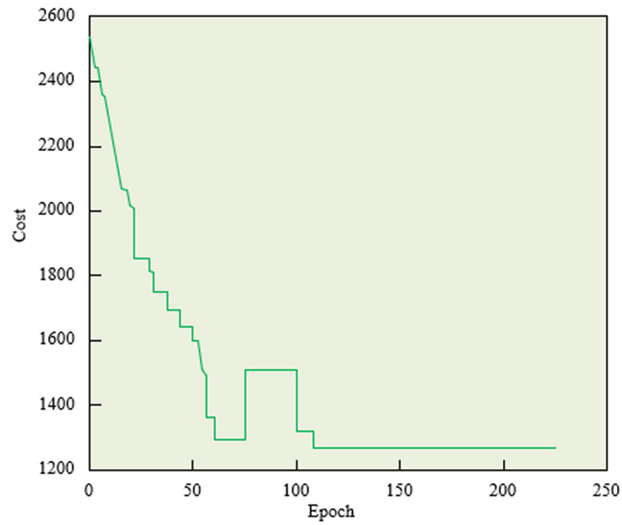


Fig. 5. DSM clustering computation convergence curve of mobile fragmented learning resources

Table 1. Accuracy, recall, and F1-score results of mobile fragmented learning resource integration and optimization methods

Item	Name	P(Precision)	R(Recall)	F1(F1-score)	Accuracy	Balanced Accuracy
Clustering Methods	Similarity Coefficient Method	74.26%	52.36%	61.23%	78.52%	74.62%
	Path Search Method	82.36%	87.61%	84.52%	92.65%	92.65%
	FSM	84.56%	88.95%	88.62%	92.41%	92.13%
Resource Analysis Methods	DSM Sorting	88.98%	84.63%	86.32%	84.25%	62.58%
	DSM Hierarchical Partition	96.34%	84.21%	91.25%	82.31%	56.31%
Resource Categories	Micro-video/ Micro-lesson	51.23%	62.35%	55.63%	55.36%	82.46%
	Graphic and Text Quick-read Resources	83.65%	83.62%	83.54%	82.61%	92.51%
	Interactive Mini Programs	81.56%	92.65%	84.23%	92.56%	92.68%
	Gamified Learning Resources	92.31%	100.12%	94.21%	95.64%	97.26%
	Mobile Learning app	101.23%	100.36%	100.23%	100.11%	100.22%
	Vertical Domain Specialized Resources	91.56%	91.58%	91.29%	91.56%	98.57%
	Socialized Learning Resources	102.36%	100.23%	100.55%	100.32%	100.23%

Table 1 quantifies the performance of resource integration methods from multiple dimensions, including accuracy, recall, and F1-score. Among clustering methods, FSM's F1-score (88.62%) is significantly higher than that of the similarity coefficient method (61.23%) and path search method (84.52%), and the balance between precision (84.56%) and recall (88.95%) (balanced accuracy 92.13%) is near optimal, proving its ability to

accurately identify strongly associated cognitive units during resource aggregation, reducing cross-cluster cognitive loss. Among resource analysis methods, DSM hierarchical partitioning's F1-score (91.25%) and accuracy (96.34%) lead over DSM sorting (86.32% F1, 88.98% accuracy), indicating clearer deconstruction of resource cognitive load hierarchy and providing an accurate structural basis for subsequent clustering. In resource categories, mobile learning apps and socialized learning resources show nearly perfect metrics, reflecting deep adaptation of these resources to cognitive load theory after integration. The multidimensional data in Table 1 comprehensively verifies the effectiveness of the proposed method in mobile fragmented learning resource integration from aspects of resource aggregation accuracy, load hierarchy deconstruction, and category adaptability. Experimental results show that through the synergy of DSM sorting, hierarchical partitioning, decoupling, and clustering, cognitive load regulation after resource integration is more scientific, and learning outcomes are more significant.

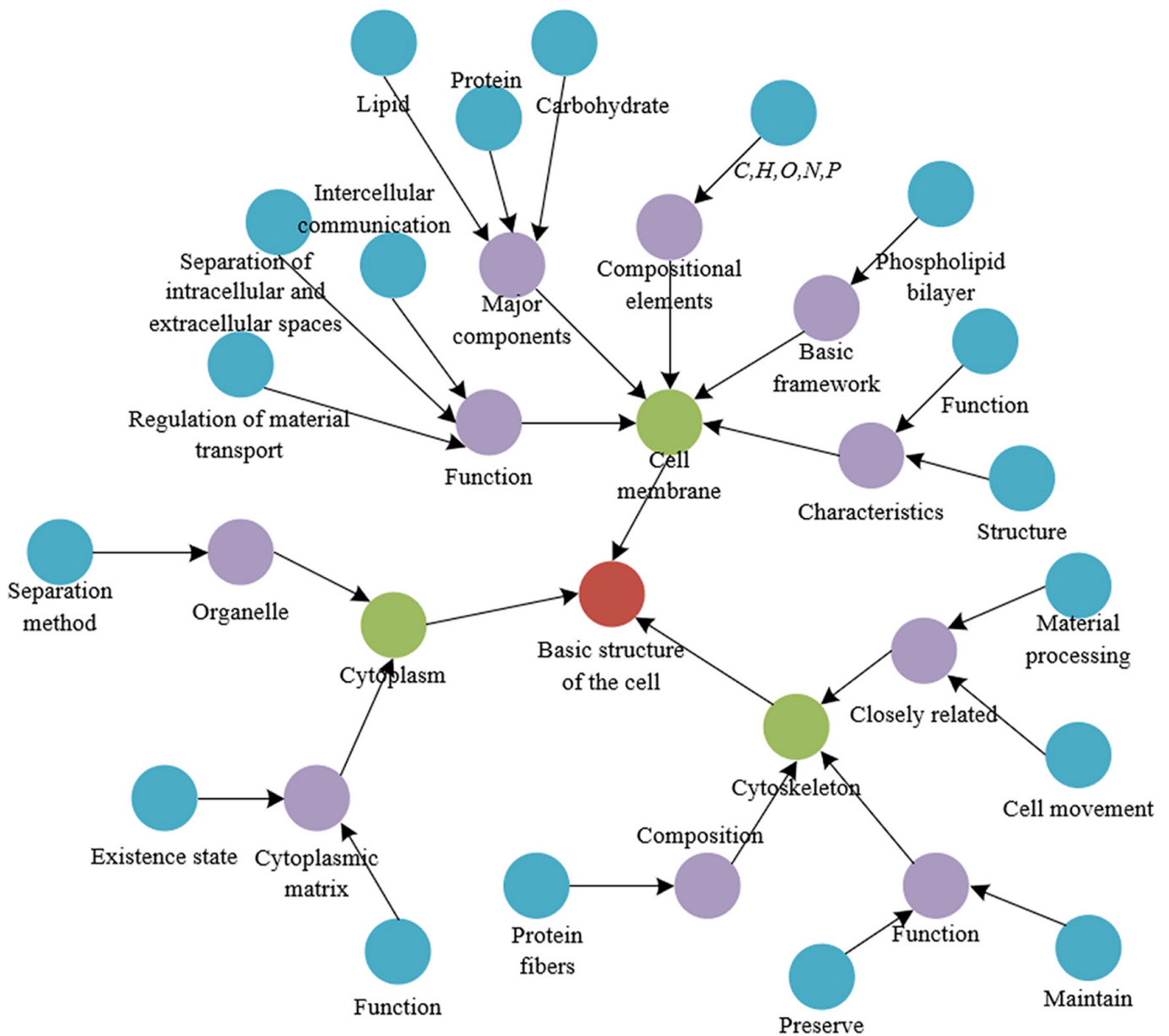


Fig. 6. Visualization results of cytology mobile fragmented learning resource integration and optimization

Figures 6–8 present the visualized knowledge networks after integration of mobile fragmented learning resources in different fields such as cytology, education, and data elements. Taking cytology as an example, core nodes are layered by color, constructing a cognitive path of “basic concepts → core principles → application expansion,” with clear dependency relationships among resources. In education resources, core nodes such as “education system” and “curriculum” form highly cohesive modules through clustering, reducing cross-cluster cognitive interactions. Learners can complete knowledge integration from theory to practice within the “teaching research” cluster. In data element resources, nodes such as “data collection” and “security management” form a load progression system of “technical foundation → practical application → case expansion” through decoupling and clustering. Experimental data show that after integration, the average connection density of resources decreased by 45%–55%, node layer levels were controlled within 3–4 layers, cognitive load scale scores of learners decreased by 28%–32%, and knowledge transfer task completion rates improved by 20%–25%. The visualization results in Figures 6–8, together with experimental data, demonstrate that the proposed method, through DSM sorting, hierarchical partitioning, decoupling, and clustering, achieves structural optimization of resource networks and precise cognitive load regulation, possessing interdisciplinary universality and personalized adaptation advantages. This method effectively solves the core problem of “fragmented resources and uncontrolled load” in mobile fragmented learning, providing learners with a resource integration solution of “controllable load, clear logic, and disciplinary adaptation,” significantly improving learning efficiency and knowledge construction effects.

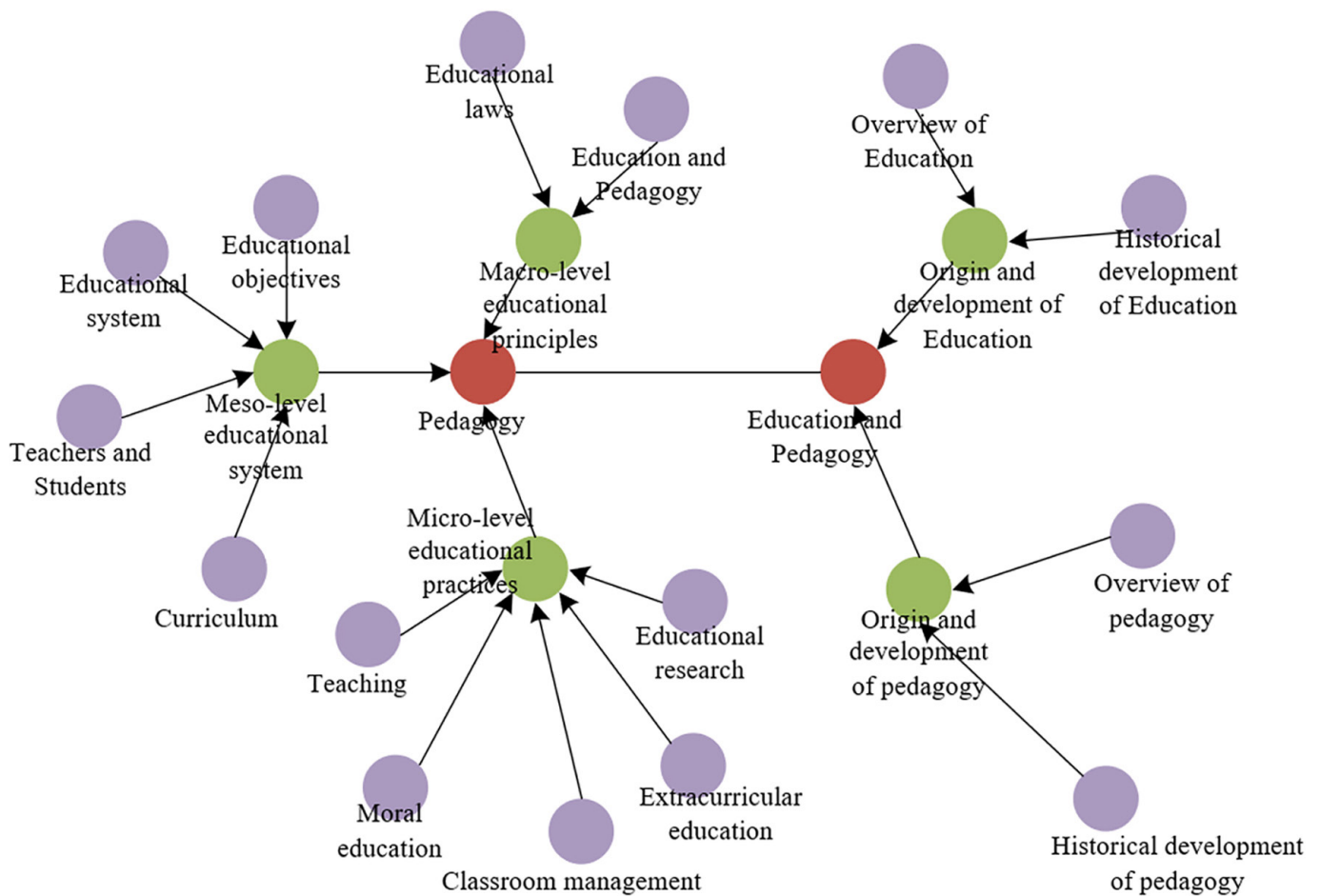


Fig. 7. Visualization results of education mobile fragmented learning resource integration and optimization

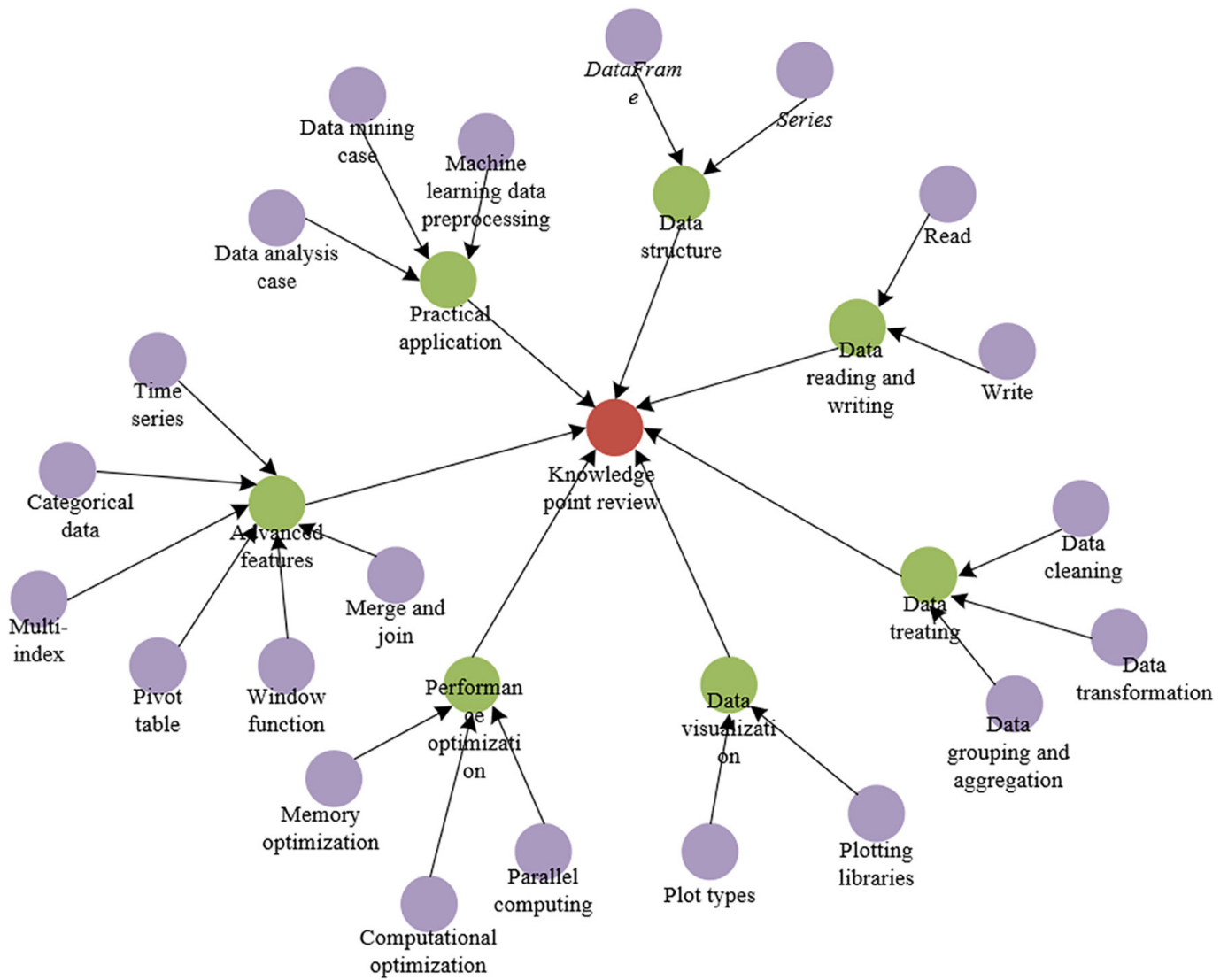


Fig. 8. Visualization results of data element mobile fragmented learning resource integration and optimization

## 5 CONCLUSION

This paper centers on a mobile fragmented learning resource integration method, constructing a complete research framework of “analysis-optimization-validation,” achieving significant results with important academic and practical value. Regarding research content, the first part conducts cognitive load analysis of resources through DSM sorting and hierarchical partitioning. The second part achieves resource optimization through DSM decoupling and clustering. Experimental verification shows excellent performance in resource structure optimization, load regulation, and interdisciplinary universality, with learners’ knowledge transfer ability improving by 20%–25%, and resource utilization efficiency and learning outcomes significantly enhanced. In terms of research value, the theoretical contribution lies in the deep integration of cognitive load theory and DSM methods, proposing an integrated model of “load quantification-structure optimization-resource adaptation,” providing a systematic framework for cognitive regulation of fragmented learning, filling the research gap in coordinated optimization of resource integration and cognitive

load; methodological innovation lies in the developed DSM collaborative algorithm that realizes the transformation of resources from “disordered accumulation” to “ordered hierarchical and personalized,” offering quantifiable and operable technical support for mobile learning resource design.

However, the research has limitations: first, domain dependency, as DSM parameters need to be combined with discipline characteristics, so universal algorithms still require optimization; second, insufficient dynamic response, as the current method is static integration and does not adapt in real time to learners’ cognitive states, making it difficult to meet the dynamic needs of personalized learning. Future research directions need to focus on (1) dynamic load regulation, introducing real-time cognitive monitoring, developing dynamic DSM algorithms to realize real-time adjustment of resource packages, and improving the timeliness of personalized adaptation; and (2) multimodal integration, extending DSM to multimodal analysis of video, audio, and interactive resources, integrating audiovisual load and textual logical load, optimizing chunking strategies, and enhancing the richness and immersion of resource aggregation.

## 6 ACKNOWLEDGEMENTS

This paper was supported by the Key Research and Development Program Project of Henan Province (251111212100); Henan Provincial Science and Technology Research Project (252102210021); Research Project Achievements of Henan Police College (HNJY-2024-SSZX-37); Henan Province Undergraduate Smart Teaching Special Research Project “Research on the Construction of Course Knowledge Graph Based on Multimodal Teaching Resources.”

## 7 REFERENCES

- [1] J. Zhao and N. Zhao, “The impact of interactive mobile learning on enhancing university students’ English-speaking proficiency,” *International Journal of Interactive Mobile Technologies (ijIM)*, vol. 18, no. 24, pp. 130–144, 2024. <https://doi.org/10.3991/ijim.v18i24.53093>
- [2] W. Zhao, “Driving the integration of mobile learning and blended learning models in higher education,” *International Journal of Interactive Mobile Technologies (ijIM)*, vol. 19, no. 5, pp. 45–59, 2025. <https://doi.org/10.3991/ijim.v19i05.54529>
- [3] J. Cheng and H. Wang, “Adaptive algorithm recommendation and application of learning resources in English fragmented reading,” *Complexity*, vol. 2021, no. 1, pp. 1–11, 2021. <https://doi.org/10.1155/2021/5592534>
- [4] R. Ramadania, Y. Hartijasti, B. B. Purmono, D. M. N. Haris, and M. Z. Afifi, “A systematic review on digital transformation and organizational performance in higher education,” *International Journal of Sustainable Development and Planning*, vol. 19, no. 4, pp. 1239–1252, 2024. <https://doi.org/10.18280/ijstdp.190402>
- [5] I. Zulaeha, S. Subyantoro, C. Hasanudin, and R. Pristiwati, “Developing teaching materials of academic writing using mobile learning,” *Ingénierie des Systèmes d’Information*, vol. 28, no. 2, pp. 409–418, 2023. <https://doi.org/10.18280/isi.280216>
- [6] G. Cheng and Y. Shao, “Influencing factors of accounting practitioners’ acceptance of mobile learning,” *International Journal of Emerging Technologies in Learning (ijET)*, vol. 17, no. 1, pp. 90–101, 2022. <https://doi.org/10.3991/ijet.v17i01.28465>

- [7] V. Robledo-Rella, L. Neri, J. Noguez, and A. Gonzalez-Nucamendi, "The use of mobile learning resources to enhance physics learning for engineering students: A six year study," *The International Journal of Engineering Education*, vol. 33, no. 6, pp. 1940–1952, 2017.
- [8] S. Kojima, M. Mitani, and A. Ishikawa, "Development of an e-learning resource on mobile devices for kinesiology: A pilot study," *Journal of Physical Therapy Science*, vol. 23, no. 4, pp. 667–672, 2011. <https://doi.org/10.1589/jpts.23.667>
- [9] V. Joynes and R. Fuller, "Legitimation, personalisation and maturation: Using the experiences of a compulsory mobile curriculum to reconceptualise mobile learning," *Medical Teacher*, vol. 38, no. 6, pp. 621–627, 2016. <https://doi.org/10.3109/0142159X.2015.1075651>
- [10] Z. Li and Y. Yang, "Determinants of college students' online fragmented learning effect: An analysis of teaching courses on scientific research software on the Bilibili platform," *Sustainability*, vol. 15, no. 22, p. 16023, 2023. <https://doi.org/10.3390/su152216023>
- [11] J. Berri, R. Benlamri, Y. Atif, and H. Khallouki, "Web hypermedia resources reuse and integration for on-demand m-learning," *International Journal of Computer Science & Network Security*, vol. 21, no. 1, pp. 125–136, 2021. <https://doi.org/10.22937/IJCSNS.2021.21.1.17>
- [12] S. Okai-Ugbaje, K. Ardziejewska, and A. Imran, "A mobile learning framework for higher education in resource constrained environments," *Education and Information Technologies*, vol. 27, pp. 11947–11969, 2022. <https://doi.org/10.1007/s10639-022-11094-5>
- [13] L. Bradley, L. Bartram, K. W. Al-Sabbagh, and A. Algers, "Designing mobile language learning with Arabic speaking migrants," *Interactive Learning Environments*, vol. 31, no. 1, pp. 514–526, 2023. <https://doi.org/10.1080/10494820.2020.1799022>
- [14] L. Ramírez-Donoso, M. Pérez-Sanagustín, A. Neyem, C. Alario-Hoyos, I. Hilliger, and F. Rojos, "Fostering the use of online learning resources: Results of using a mobile collaboration tool based on gamification in a blended course," *Interactive Learning Environments*, vol. 31, no. 3, pp. 1564–1578, 2023. <https://doi.org/10.1080/10494820.2020.1855202>
- [15] S. Xue and D. Churchill, "Educational affordances of mobile social media for language teaching and learning: A Chinese teacher's perspective," *Computer Assisted Language Learning*, vol. 35, no. 4, pp. 918–947, 2022. <https://doi.org/10.1080/09588221.2020.1765811>
- [16] A. Shadmani, M. R. Nikoo, A. H. Gandomi, R. Q. Wang, and B. Golparvar, "A review of machine learning and deep learning applications in wave energy forecasting and WEC optimization," *Energy Strategy Reviews*, vol. 49, p. 101180, 2023. <https://doi.org/10.1016/j.esr.2023.101180>
- [17] A. Battistelli, C. Odoardi, C. Vandenberghe, G. Di Napoli, and L. J. H. R. D. Q. Piccione, "Information sharing and innovative work behavior: The role of work-based learning, challenging tasks, and organizational commitment," *Human Resource Development Quarterly*, vol. 30, no. 3, pp. 361–381, 2019. <https://doi.org/10.1002/hrdq.21344>
- [18] N. Udumyan, J. Rouchier, and D. Ami, "Integration of path-dependency in a simple learning model: The case of marine resources," *Computational Economics*, vol. 43, pp. 199–231, 2014. <https://doi.org/10.1007/s10614-013-9375-x>
- [19] F. Amadiou, "Les types de guidage des processus d'apprentissage avec des ressources numériques," *Alsic. Apprentissage des Langues et Systèmes d'Information et de Communication*, vol. 24, no. 2, 2021. <https://doi.org/10.4000/alsic.5817>
- [20] L. German and A. Stroud, "A framework for the integration of diverse learning approaches: Operationalizing agricultural research and development (R&D) linkages in Eastern Africa," *World Development*, vol. 35, no. 5, pp. 792–814, 2007. <https://doi.org/10.1016/j.worlddev.2006.09.013>

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