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PAPER

# A Mobile Technology-Based Framework for Digital Libraries: Bridging Accessibility and Personalized Learning

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**ABSTRACT**

With the rapid development of mobile technology, digital libraries have become critical platforms for supporting education and academic research. However, traditional digital libraries face significant challenges in terms of accessibility on mobile devices and personalized learning support. In particular, existing technologies and research have yet to comprehensively address the need for meeting diverse reader requirements and enhancing the convenience and flexibility of information access. Against this backdrop, a mobile technology-based digital library framework was proposed in this study, aimed at improving the reader experience and promoting personalized learning through accessibility-assistance tools and personalized learning path recommendation systems. Specifically, the study focuses on two core components: (a) the design of accessibility-assistance tools for mobile digital libraries, ensuring that diverse readers, particularly those with special needs, can easily access information; and (b) the development of personalized learning path recommendation methods, integrating readers' interest points with learning themes to achieve more precise and intelligent learning support. By integrating mobile technology with intelligent recommendation algorithms, innovative applications within the digital library domain were explored, with the goal of offering new insights into enhancing the quality of digital library services and learning efficiency.

**KEYWORDS**

mobile technology, digital libraries, accessibility, personalized learning, learning path recommendation, intelligent recommendation algorithms

## 1 INTRODUCTION

With the rapid advancement of information technology, as essential resources for modern education and research, digital libraries have gradually become significant platforms for academic, cultural, and knowledge dissemination. The widespread application of mobile technology, in particular, has introduced new opportunities

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and challenges for the construction and development of digital libraries [1–4]. With the aid of mobile devices, readers can access vast electronic resources anytime and anywhere, offering greater convenience and flexibility in information retrieval [5, 6]. This transformation not only enhances the efficiency of digital library usage but also provides readers with more personalized and customized learning experiences. However, as the volume of resources grows and reader needs become increasingly diverse, ensuring accessibility and achieving efficient personalized learning path recommendations in mobile digital libraries remain key challenges in current research.

Although some studies have explored the accessibility and personalized recommendations of digital libraries, the existing methods and technologies still exhibit several shortcomings [7–11]. For example, many current systems focus more on accessibility in traditional desktop environments, with limited attention given to designing accessibility features for mobile devices [12, 13]. Additionally, personalized learning path recommendations often rely solely on basic reader information and fail to deeply integrate readers' interest points with learning themes, which limits both the accuracy and practicality of the recommendations [14, 15]. More importantly, existing research tends to focus on isolated domains and lacks a cross-disciplinary, systematic theoretical framework, making it difficult to meet the diverse needs of readers [16–20].

This study aims to propose a mobile technology-based digital library framework, with a focus on two main research areas. On one hand, the design and development of accessibility-assistance tools for mobile digital libraries were explored to ensure that all readers, particularly those with special needs, can successfully access the resources provided by the platform. On the other hand, how to construct a personalized learning path recommendation system was investigated based on the deep integration of readers' interest points and learning themes, aiming to enhance the learning experience and efficiency. Through these two areas of research, the goal is to advance the depth and breadth of digital library-related studies from a theoretical perspective while also providing new ideas and solutions for creating more intelligent and efficient learning platforms in practice.

## 2 ACCESSIBILITY-ASSISTANCE TOOLS FOR MOBILE DIGITAL LIBRARIES

To better meet the needs of different types of readers, an overall framework for enhancing the accessibility of mobile digital libraries, based on large language models, was proposed. This framework aims to overcome barriers encountered by readers, particularly those with special needs, during their interaction with digital libraries through intelligent means. The framework achieves accessibility enhancement by obtaining data from three primary sources: reader requirements, historical records, and Graphical User Interface (GUI) observations. In the core of the framework, reader needs were first analyzed to identify personalized requirements and preferences. Subsequently, historical behavioral data was extracted from readers' past interactions to infer potential needs and optimize service content based on reader-system interaction history. At the same time, GUI elements were observed and analyzed to obtain information on the interface layout and element status. The integration of these data sources offers rich contextual information for the subsequent use of a large language model. After constructing appropriate prompts, the gathered information was input into the language model, generating a series of highly targeted and reader-needs-matched User Interface (UI) commands.

After the decision was generated by the large language model, the output UI commands were further filtered through an output filter to ensure their precision and operability. The filter's role is to optimize the large language model's output based on specific rules and context, preventing the generation of ineffective or inaccurate commands, thereby ensuring that the results can genuinely address the accessibility issues faced by readers. The filtered UI commands were then directly passed to the accessibility-assistance tools within the mobile application. These tools interact with the GUI, adjusting the content and functionality of the interface in real time to ensure that information is presented to readers in the most suitable form. Moreover, all generated decision commands and the interaction history with readers were recorded for future use, forming a closed-loop feedback mechanism.

In this framework, capturing readers' interest points and the learning themes that they are interested in is a key step in enhancing the personalized experience. The system can identify long-term themes and preferences by analyzing readers' historical data. This data includes browsing trajectories, search histories, and interaction records with digital resources in the mobile digital libraries, such as the books and articles that readers have accessed and the access frequency of related resources. Based on the data, the system can construct a reader interest map that captures the domains, research directions, and learning goals of the reader. Additionally, real-time feedback from readers, such as search behavior and tag selection, can dynamically update the interest points and learning themes. This information is processed and analyzed by the large language model to help the system understand and predict changes in readers' interests, thereby offering more personalized and accurate resource recommendations. In this way, both accessibility is enhanced, and learning effectiveness is improved. Figure 1 presents the personalized learning path recommendation framework for the mobile library proposed in this study.

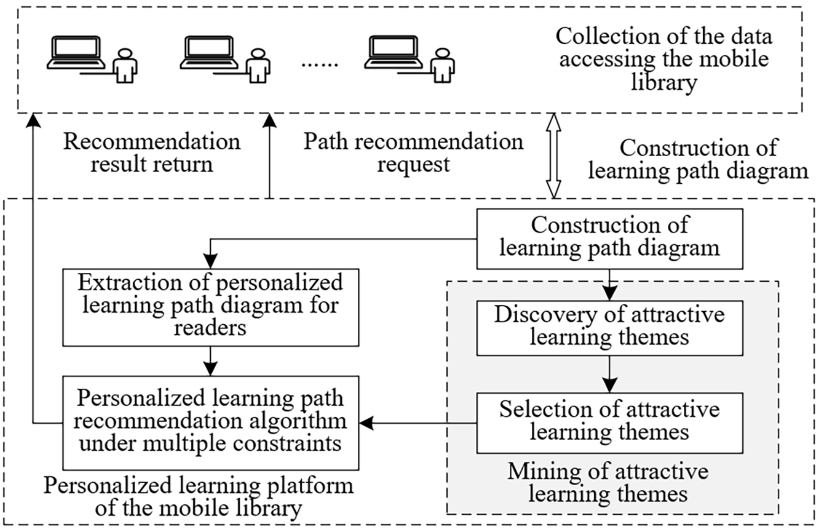


**Fig. 1.** Personalized learning path recommendation framework for the mobile library

## 3 PERSONALIZED LEARNING PATH RECOMMENDATION BASED ON INTEREST POINTS

Based on dynamically updated interest points, a personalized learning path recommendation for digital libraries was attempted in this study. The path recommendation problem was first defined.

A learning path graph is represented as a weighted directed graph $H = (N, \gamma)$, where $N = \{n_1, n_2, \ldots, n_v\}$ is the set of interest points, which represents various themes or resource areas within the digital library. Each interest point represents a knowledge domain or learning theme that may interest the reader, and an edge $r_{uk} \in \gamma$ indicates a learning path from interest point $n_u$ to interest point $n_k$, representing the potential path from one interest point to another. The edge weights in the graph reflect the average travel time required for learning along the path, which is the transition time between two interest points for the reader. The time includes both the physical transition time between the interest points as well as the cognitive load time required by the reader during the learning process.

Preference is a key concept used to quantify the reader's inclination towards different interest points or learning themes. The preference attribute of each reader $i$ and interest point $n$ is mapped to a $c$-dimensional category space, represented as preference vectors $O(i)$ and $O(n)$, where each element $\varepsilon_u$ in the vector represents the weight of that category within the corresponding vector. Specifically, the preference vector $O(i)$ indicates the strength of reader $i$'s interest degree in various knowledge themes, with the value of $\varepsilon_u$ ranging from 0 to 1. A higher value of $\varepsilon_u$ indicates a stronger interest by the reader in that category. The preference vector $O(n)$, on the other hand, indicates the degree to which interest point $n$ belongs to each category, reflecting how well the content of that interest point aligns with a particular category. The construction of the preference vectors is based on the reader's historical access records. Specifically, the reader's preference for a given category is estimated by calculating the ratio of visits to interest points within that category to the total number of visits.

The preference degree refers to the strength of interest or preference that reader $i$ has for each interest point $n$. It is quantified by calculating the similarity between the reader's preference vector $O(i)$ and the interest point's preference vector $O(n)$. The preference degree can be calculated using the cosine similarity formula. Given $O(i) = (\beta_1, \beta_2, \ldots, \beta_c)$ and $O(n) = (\alpha_1, \alpha_2, \ldots, \alpha_c)$, the calculation of $ot(i, n)$ is as follows:

$$ot(i,n) = \frac{\sum_{u=1}^{c} \beta_u \cdot \alpha_u}{\sqrt{\sum_{u=1}^{c} \beta_u^2} \cdot \sqrt{\sum_{u=1}^{c} \alpha_u^2}} \tag{1}$$

This similarity value reflects the degree of preference that the reader has for the interest point. The value closer to 1 indicates a higher matching degree between the reader and the interest point, meaning a stronger preference. By calculating the preference degree, the digital library can accurately determine which interest points best match the reader's needs.

A learning path refers to a sequence of ordered interest points that guide the reader from one interest point to another. A learning path can consist of one or more interest points and is represented as $so = (n_{j1}, n_{j2}, \ldots, n_{jt})$, where $t$ represents the number of interest points in the path. Each learning path represents a specific order of knowledge acquisition, and readers can choose different paths to follow based on their interests and learning objectives. In the path, each interest point $n$ has an associated dwell time $S(i, n)$, which is estimated based on the reader's past learning time spent at that interest point. This dwell time reflects the depth of the reader's engagement with that interest point. Additionally, the transition time $r_{uk}$ between interest points is estimated using factors such as Euclidean distance and walking speed. The total time required to complete a learning path is denoted by the function $S(i, so)$, and the calculation formula is:

$$S(i,so) = \sum_{u=1}^{t-1} \sum_{k=2}^{t} s(r_{uk}) + \sum_{u=1}^{t} S(i,n_k) \tag{2}$$

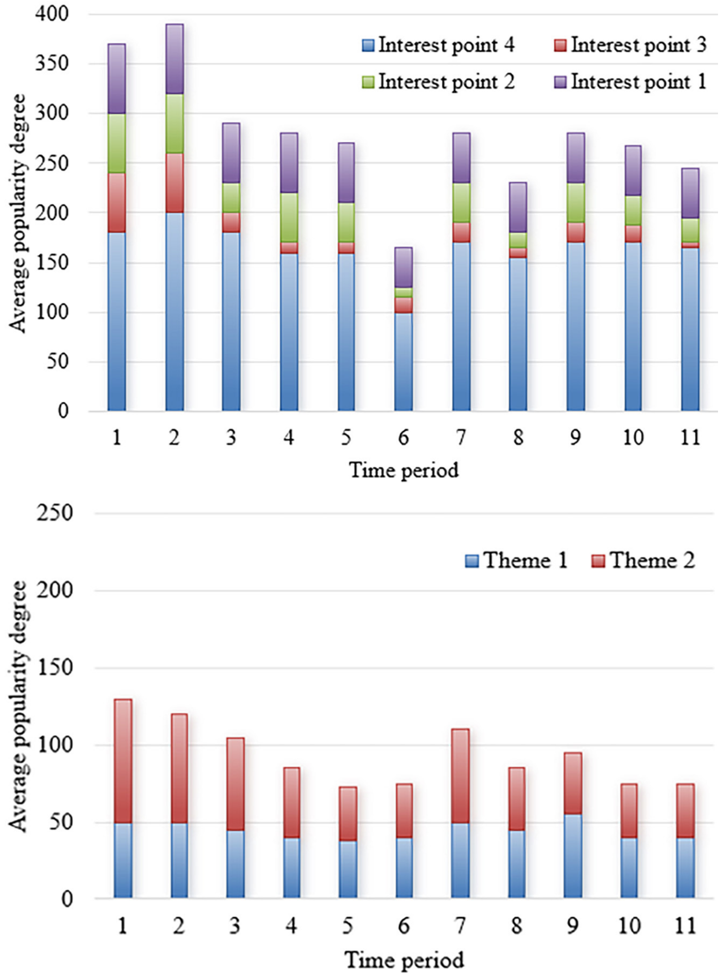


**Fig. 2.** Popularity of learning themes corresponding to different interest points in practical application scenarios

Figure 2 shows the popularity of learning themes corresponding to different interest points in practical application scenarios. Traditional interest point recommendations are typically based on the reader's personal interests and historical behavior. However, the quality of a learning path is not solely determined by the interest points themselves but is also greatly influenced by the attractiveness of the learning themes. Attractive learning themes are those that can stimulate the reader's curiosity and interest in learning. They not only hold unique appeal for individual readers but also enhance the attractiveness and coherence of the learning path by providing content related to the interest points. Based on this, personalized learning path recommendations should not only consider transitions and relationships between interest points but also optimize the learning themes within the path to enhance its appeal, thus ensuring that the recommended learning paths better align with the reader's needs and psychological expectations.

Specifically, the experience of reader $i$ at interest point $n$ can be quantified by comprehensively considering attributes such as the content quality, difficulty, and relevance of the interest point, as well as the reader's preference degree for that point. Each interest point $n$ includes a series of attributes, such as the learning themes covered, the depth and breadth of knowledge, and the availability of learning resources.

These attributes determine the intrinsic value of the interest point. Let the rating of interest point $n$ be represented by $ET(n)$, and the preference degree for the interest point is defined as:

$$R(i,n) = ot(i,n) \cdot ET(n) \tag{3}$$

The reader's experience on a learning path is the sum of the experiences at each interest point along the path:

$$R(i,so) = \sum_{n \in so} R(i,n) \tag{4}$$

The personalized path recommendation problem based on interest points aims to identify the optimal path that maximizes the reader's experience. This can be formulated as an optimization problem:

$$\begin{aligned} MAX \quad & R(i,so) \\ s.t \quad & S(i,so) \leq F \end{aligned} \tag{5}$$

Traditional interest point recommendations are typically based on the reader's personal interests and historical behavior. However, the quality of a learning path is not solely determined by the interest points themselves but is also significantly influenced by the attractiveness of the learning themes. Attractive learning themes refer to those that can stimulate the reader's curiosity and interest in learning. They not only hold unique appeal for individual readers but also enhance the attractiveness and coherence of the learning path by providing content related to the interest points. For example, if a learning path contains highly attractive learning themes, it can not only make the reader more interested in the path but also add enjoyment to the overall experience, thereby enhancing the reader's sense of involvement and satisfaction. Let the preference degree of reader $i$ for learning theme $r$ be denoted as $ot(i, r)$, and the rating of $r$ be represented by $ET(r)$. The reader experience of reader $i$ upon accessing $r$ is calculated as:

$$R(i,r) = ot(i,r) \cdot ET(r) \tag{6}$$

$R(i, so)$ represents the reader experience of reader $i$ on path $so$ and can be calculated as follows:

$$R(i,so) = \sum_{u=1}^{v-1} \sum_{k=2}^{v} a_{uk} \left( R(i,n_k) + R(i,e_{uk}) \right) \tag{7}$$

The personalized learning path recommendation problem, integrating interest points and learning themes, was defined as recommending the optimal learning path within a given learning path graph $H = (N, \gamma)$ that satisfies specific reader needs and constraints. Learning themes reflect the reader's interests and learning preferences, while learning paths are constituted by the connections between interest points. For each reader $i$, the recommended learning path should take into account the reader's learning goals, interests, time constraints, and experience requirements. Specifically, the personalized recommendation task requires the recommendation of a learning path $so$ that satisfies the reader's request, including the start point, time constraint $S_{MAX}$, planned interest point types, and minimum reader experience $\sigma$. During this process, the objective of learning path recommendation is to maximize the reader's experience while ensuring that the path meets the following four constraints:

**a)** The learning path must begin at a specified starting point to ensure the directionality of the path.
**b)** The recommended learning path should consist of a series of connected interest points, without any loops, to avoid redundancy and inefficiency in the path.
**c)** The total time for the learning path must remain within the defined maximum time $S_{MAX}$ to ensure the feasibility and rationality of the path.
**d)** The reader experience for the recommended path must be greater than or equal to the pre-defined minimum reader experience requirement $\sigma$, ensuring that the recommendation genuinely meets the reader's learning needs and interests.

Therefore, the formal definition of this problem is as follows:

$$MAX \quad R(i, so) \tag{8}$$

$$s.t. \quad \sum_{u=2}^{v} a_{1u} = 1 \tag{9}$$

$$\sum_{u=1}^{v-1} a_{uj} = \sigma \sum_{k=2}^{v} a_{uj} \leq 1 \tag{10}$$

$$\sum_{u=1}^{v-1} \sum_{k=2}^{v} a_{uk} \left( S(i, r_{uk}) + S(i, n_k) \right) \leq S_{MAX} \tag{11}$$

$$\sum_{u=1}^{v-1} \sum_{k=2}^{v} a_{uk} R(i, n_k) \geq \sigma \tag{12}$$

## 4 PERSONALIZED LEARNING PATH RECOMMENDATION BASED ON THE INTEGRATION OF INTEREST POINTS AND LEARNING THEMES

In the algorithm proposed in this study, the integration of interest points and learning themes is key to achieving accurate recommendations. For a particular interest point in a mobile library, the popularity of the learning themes associated with this interest point may be uneven. To address this, the Gini coefficient was introduced in this study. In a learning path graph, let the proportion of the popularity of the edge $r_{uk}$ in the interest point $n_k$ be denoted by $o_{uk}$. A vector $\vec{o}_k = [o_{1k}, o_{2k}, \ldots]$ was defined, where the elements are arranged in ascending order. The Gini coefficient $GINI\left(\vec{o}_k\right)$ for the interest point $n_k$ is calculated as follows:

$$GINI\left(\vec{o}_k\right) = 1 - \frac{1}{\left|\vec{o}_k\right|} \left( 2 \cdot \sum_{u=1}^{\left|\vec{o}_k\right|} \sum_{j=1}^{u} o_{jk} - 1 \right) \tag{13}$$

The process of discovering attractive learning themes is as follows: an empty set $E$ is first initialized, and the reader's interest point $n_k$ is analyzed step by step. Then the popularity and Gini coefficient are calculated. This process not only helps identify the themes most appealing to the reader but also selects the interest points with both high popularity and large Gini coefficients using predefined thresholds $\lambda_1$ and $\lambda_2$. This method ensures that the recommended learning themes are not only aligned with the reader's interests but also possess a certain degree of diversity and fairness.

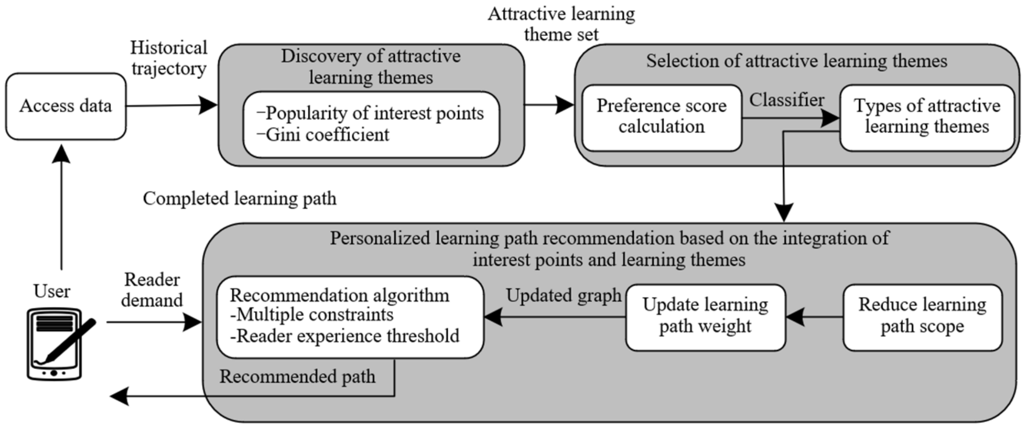


**Fig. 3.** Personalized learning path recommendation framework based on the integration of interest points and learning themes

Figure 3 illustrates the personalized learning path recommendation framework based on the integration of interest points and learning themes. The algorithm proposed in this study constructs a learning path graph, denoted as $H = (N, \gamma)$, where all interest points are mapped as nodes $N$ in the graph, and the relationships and connections between interest points are represented by the edges $\gamma$. This learning path graph not only considers the connections between interest points but also incorporates readers' time constraints and the accessibility of interest points, especially situations where certain interest points may be inaccessible during specific time periods. To recommend the most suitable learning path within a limited time frame, the system calculates the preference scores for each interest point based on the reader's preference vector $O(i)$ and the preference vector $O(n)$ for each interest point. These preference scores allow the recommendation system to identify which interest points are most likely to attract the reader, thereby narrowing the search space and selecting the top $j$ most interesting interest points. These selected interest points form a new learning path graph $H'$, where $N$ is a subset of the nodes corresponding to the selected interest points, and $\gamma$ represents the set of learning themes between these interest points, forming a more focused and personalized subgraph.

In the personalized learning path recommendation system for mobile libraries, for each attractive learning theme in the intersection $\gamma' \cap E$, the reader $i$'s interest preference $O(i)$ is mapped into the category space. If $O(i)$ falls within the region corresponding to $e_{ij}$, the reader's experience and time expenditure on learning theme $r$ in graph $H'$ will be updated. The reader's experience on $r_{uk}$ is updated to $R(i, r_{uk})$. The indicator function is denoted as $U_{i \to r_{uk}}$, and the difference in average time expenditure between readers who like $r_{uk}$ and those who do not is characterized by $\Delta S(i, r_{uk})$. The time expenditure $S(i, r_{uk})$ is updated as follows:

$$S(i, r_{uk}) = s(r_{uk}) + U_{i \to r_{uk}} \Delta S(i, r_{uk}) \tag{14}$$

The updated itinerary graph is represented as $H''(i)$, which is a personalized graph customized for reader $i$.

## 5 EXPERIMENTAL RESULTS AND ANALYSIS

In the experiment, the distribution of the Gini coefficients of interest points was computed to examine the distribution characteristics of different interest points within the platform. Figure 4 shows the Gini coefficient distribution of interest points, where interest points with larger Gini coefficients correspond to lower probability densities. This indicates that these interest points are relatively sparsely distributed, and reader interest is more diffusely concentrated. To further analyze the filtering and recommendation effects of interest points, two thresholds, $\lambda_1$ and $\lambda_2$, were set at 800 and 0.3, respectively, and experimental validation was conducted. In the experiment, with $\lambda_1$ set at 800, approximately 10% of interest points were successfully filtered out. This means that after threshold adjustment, the system was able to remove a portion of low-frequency interest points that did not attract enough reader attention, thereby improving the efficiency and accuracy of the recommendation system.

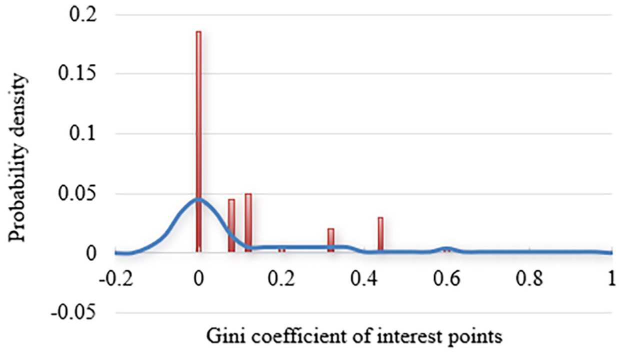


**Fig. 4.** Gini coefficient distribution of interest points in the real dataset

Figure 5 illustrates the distribution of interest points connected to attractive learning themes. Specifically, the connections between interest points and learning themes were analyzed, with a focus on the degree of association between these interest points and attractive learning themes. From the experimental results, it was observed that among interest points with four incoming edges, the majority of them had at least one edge connected to an attractive learning theme. This suggests that most interest points have complex relationships with learning themes, particularly those with multiple incoming edges, which may encompass multiple learning themes, thereby enhancing the aggregation and recommendation capabilities of the learning content.

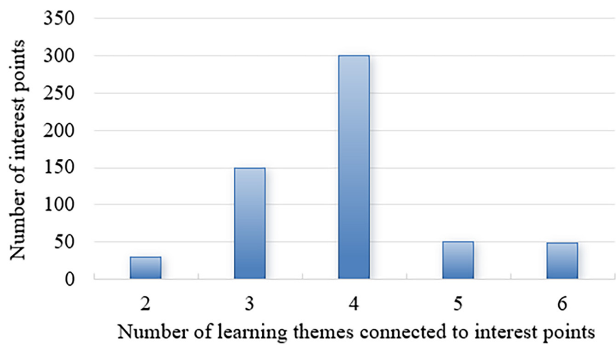


**Fig. 5.** Distribution of interest points connected to attractive learning themes in the real dataset

According to the experimental results presented in Figure 6, significant differences in execution time were observed between the proposed method and other algorithms, namely Neural Collaborative Filtering (NCF), Deep Factorization Machine (DFM), and Graph Neural Network (GNN), across various time limits and datasets.

For the fitting dataset, as the time limit increased, the execution time of the proposed method remained relatively stable around 0.19. In contrast, the execution time of NCF increased from 0.055 to 0.18, showing a gradual upward trend. The execution time of DFM was relatively low across the entire range but exhibited some fluctuations, with a maximum value of 0.13. The execution time of GNN remained fairly constant, ranging from 0.01 to 0.015, significantly lower than that of the other algorithms. For the real dataset, regardless of changes in the time limit, the execution times of both the proposed method and NCF remained constant at 0.25, unaffected by the time limit. On the other hand, the execution time of DFM and GNN was relatively close, both around 0.28. From the experimental results, it can be concluded that the proposed method exhibits a high level of stability in execution time on the fitting dataset, effectively handling varying time limits without significant fluctuations in execution time. This suggests that the proposed method demonstrates strong optimization ability and efficiency when processing datasets with higher complexity.

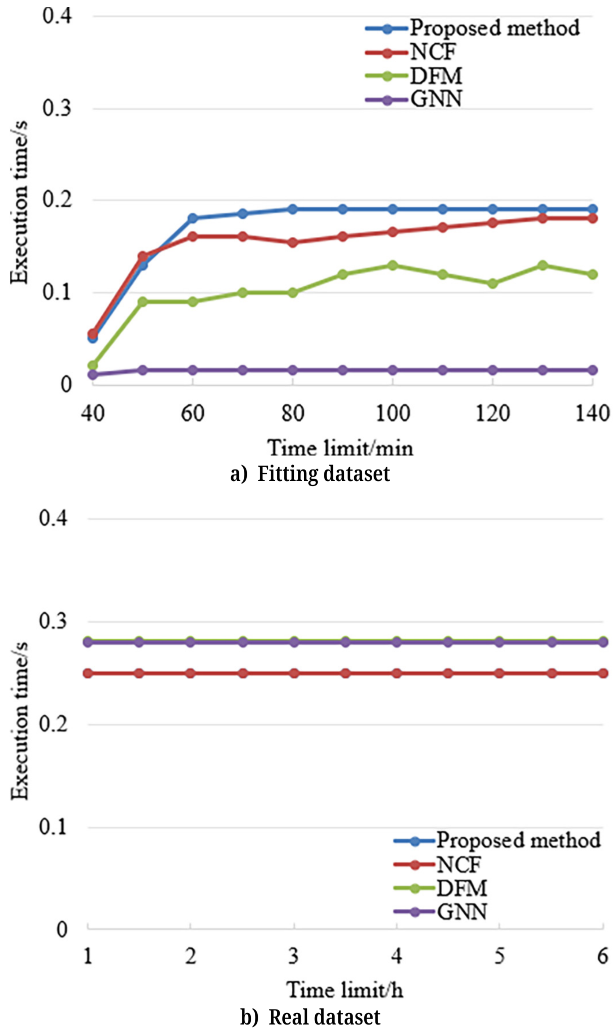


**Fig. 6.** Algorithm execution time on different datasets

According to the experimental data presented in Figure 7, significant differences in execution time were observed between the proposed method and other algorithms (NCF, DFM, and GNN) for both the fitting dataset and the real dataset. For the fitting dataset, the execution time of the proposed method exhibited a generally stable increase under varying time limits. Initially, the time was 8 seconds, and as the time limit increased, the execution time progressively rose, reaching a maximum of 22 seconds, after which it stabilized. In comparison, the execution time of NCF grew more gradually, increasing from 10 seconds to 19 seconds, with a relatively small overall variation. The execution time of DFM and GNN, however, showed a larger increase, especially for GNN, which increased from 20 seconds to 27.5 seconds, indicating a significant rise in execution time as the dataset complexity increased. For the real dataset, the proposed method demonstrated relatively stable execution time, ranging from a minimum of 1 second to a maximum of 4 seconds, with minimal influence from the time limit. In contrast, the execution time of NCF, DFM, and GNN exhibited significant changes with increasing time limits, particularly GNN, whose execution time increased sharply from 62.5 seconds to 88 seconds, showing more pronounced fluctuations in execution time.

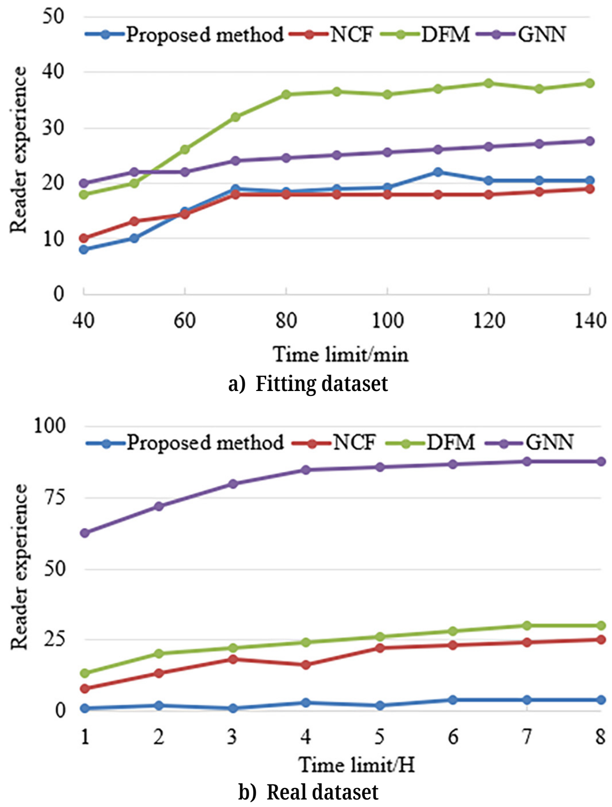


**Fig. 7.** Impact of time limit on reader experience of learning paths

The experimental results suggest that the proposed method exhibits a relatively stable increase in execution time when handling the fitting dataset, indicating that it can balance time efficiency and computational demands well when dealing with more complex datasets. This makes it suitable for providing stable services in time-constrained environments. This characteristic is especially beneficial for personalized learning path recommendation systems in digital libraries, as it can offer efficient learning experiences to readers. For the real dataset, the proposed method showed minimal variation in execution time, reflecting its strong adaptability to different learning themes or interest points, enabling it to complete recommendation tasks in a short time with good flexibility. In comparison, methods such as NCF, DFM, and GNN exhibited significant fluctuations in execution time, with GNN performing particularly poorly under a high time limit, with a substantial increase in execution time that could potentially degrade the learning experience.

**Table 1.** Performance analysis of different algorithms on different datasets

| Dataset | Real Dataset | | | | Fitting Dataset | | | |
|---|---|---|---|---|---|---|---|---|
| Algorithm | GNN | DFM | NCF | Proposed Method | GNN | DFM | NCF | Proposed Method |
| $R@3$ | 0.1235 | 0.1258 | 0.1562 | 0.2895 | 0.1215 | 0.1124 | 0.1562 | 0.2785 |
| $R@5$ | 0.1252 | 0.1325 | 0.1785 | 0.3562 | 0.1215 | 0.1235 | 0.1785 | 0.3625 |
| $R@10$ | 0.1232 | 0.1658 | 0.2652 | 0.4325 | 0.1325 | 0.1562 | 0.2451 | 0.4125 |
| $R@15$ | 0.1625 | 0.2215 | 0.3125 | 0.4582 | 0.1562 | 0.2125 | 0.2636 | 0.4125 |
| $P@3$ | 0.2125 | 0.2231 | 0.3256 | 0.4215 | 0.2236 | 0.2215 | 0.3125 | 0.4125 |
| $P@5$ | 0.1785 | 0.1754 | 0.3125 | 0.3526 | 0.1785 | 0.1625 | 0.2895 | 0.3452 |
| $P@10$ | 0.1452 | 0.1526 | 0.2563 | 0.2536 | 0.1452 | 0.1456 | 0.2536 | 0.2563 |
| $P@15$ | 0.1215 | 0.1625 | 0.1625 | 0.2236 | 0.1242 | 0.1236 | 0.1526 | 0.2136 |
| $F1@3$ | 0.1325 | 0.1526 | 0.2241 | 0.3562 | 0.1325 | 0.1325 | 0.2126 | 0.3458 |
| $F1@5$ | 0.1326 | 0.1526 | 0.2215 | 0.3569 | 0.1425 | 0.1426 | 0.2236 | 0.3485 |
| $F1@10$ | 0.1325 | 0.1562 | 0.2639 | 0.3254 | 0.1225 | 0.1458 | 0.2456 | 0.3125 |
| $F1@15$ | 0.1325 | 0.1625 | 0.2152 | 0.3245 | 0.1212 | 0.1562 | 0.2125 | 0.2896 |

According to the data presented in Table 1, the proposed method demonstrates significantly superior performance over other algorithms on both the real and fitting datasets. For the real dataset, the proposed method excels across multiple metrics, particularly in $R@3$, $R@5$, and $R@10$, where the values are 0.2895, 0.3562, and 0.4325, respectively, all of which are considerably higher than those of the other algorithms. For instance, GNN achieves a value of only 0.1235 for $R@3$, while DFM and NCF have values of 0.1258 and 0.1562, respectively, indicating weaker performance. The proposed method also maintains high performance on metrics such as $P@3$ and $P@5$, with values of 0.4215 and 0.3526, respectively, leading other algorithms. On the fitting dataset, the proposed method also shows stable performance, particularly in $R@3$, $R@5$, and $R@10$, with values of 0.2785, 0.3625, and 0.4125, respectively, outperforming GNN ($R@3$ = 0.1215, $R@5$ = 0.1215) and DFM ($R@3$ = 0.1124, $R@5$ = 0.1235). The F1-score further indicates that the proposed method achieves stronger recommendation quality on both the real and fitting datasets, with $F1@3$ and $F1@5$ values surpassing those of the other methods.

**Table 2.** Algorithm comparison before and after the integration of learning themes

| Algorithm | Recall | Precision | F1-Score |
|---|---|---|---|
| Before integration | 0.139 | 0.225 | 0.178 |
| After integration | 0.232 | 0.148 | 0.123 |

According to the data presented in Table 2, the proposed method demonstrates significant improvements in recall, precision, and F1-score after the integration of learning themes. Prior to integration, the recall was 0.139, precision was 0.225, and the F1 score was 0.178. After the integration, recall increased to 0.232, while precision decreased to 0.148, and the F1 score dropped to 0.123. This result indicates that the integration of learning themes improved recall but led to a reduction in precision. Specifically, the increase in recall after integration suggests that the algorithm is able to capture a broader range of relevant learning resources, whereas the decrease in precision may indicate that, while more resources are being recommended, some of the recommended resources may not fully match the reader's actual interest points, leading to a slight reduction in recommendation accuracy. The experimental results suggest that the integration of learning themes was successful in improving recall, indicating that the learning path recommendation system can successfully expand its coverage of potentially relevant content.

## 6 CONCLUSION

The mobile technology-based digital library framework proposed in this study demonstrates significant innovation and practical value in addressing learning path recommendations and enhancing platform accessibility. This study focuses on two key areas. On one hand, accessibility-assistance tools were designed and developed to support all readers, especially those with special needs, ensuring their smooth use of the digital library platform and enabling full utilization of the platform's resources for learning. On the other hand, the study explored how the deep integration of readers' interest points and learning themes could be leveraged to construct a personalized learning path recommendation system. Experimental results show that the proposed personalized recommendation method achieves superior recommendation performance across various datasets, particularly excelling in metrics such as recall and F1 score, outperforming traditional algorithms such as GNN, DFM, and NCF, and demonstrating strong recommendation accuracy and stability. By integrating learning themes, the system not only improves recall but also broadens the coverage of potentially relevant content, thereby providing readers with a more comprehensive personalized learning path. While recall improves, a slight decrease in precision can be observed. However, this result offers a basis for further optimizing personalized recommendations.

The study provides robust technical support for the development of mobile digital libraries, with high practical value in enhancing personalized learning recommendations and platform accessibility. Firstly, the personalized recommendation system, through the deep integration of readers' interest points and learning themes, optimizes recommendation outcomes, thereby effectively improving learning efficiency and enhancing the learning experience, which holds significant implications for the future development of educational technology. Secondly, the design of accessibility-assistance tools ensures the participation of special needs groups in learning, providing technical support for the widespread adoption and equity of digital libraries.

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