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PAPER

Integrating Mobile Technology into Accounting Practice Instruction: A Strategy for Application and Exploration of Educational Value

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ABSTRACT

Amid the rapid advancement of mobile technology and the ongoing digital transformation of education, accounting practice instruction has encountered persistent challenges, including the disconnection between theoretical frameworks and practical application and delays in updating instructional resources. Although prior research has demonstrated the potential of mobile technology in this field, limitations remain in aligning technological tools with the construction of knowledge systems. Moreover, fragmented learning experiences often lack systematic integration, and existing knowledge delivery mechanisms exhibit insufficient contextual relevance. To address these issues, this study focuses on the integration of mobile technology within accounting practice instruction. A knowledge graph for accounting practice instruction grounded in mobile technology was proposed, alongside a strategy for the targeted delivery of fragmented knowledge. By restructuring the accounting practice knowledge system and leveraging the visualization and intelligent capabilities of mobile technology, the study seeks to achieve systematic knowledge construction and personalized knowledge delivery. These efforts are intended to enhance the practicality, relevance, and adaptability of accounting practice instruction, thereby underscoring the educational value of mobile technology in the domain of accounting education.

KEYWORDS

mobile technology, accounting practice instruction, knowledge graph, fragmented knowledge delivery, educational value

1 INTRODUCTION

In the context of a global digital transformation, mobile technology-characterized by its portability, interactivity, and real-time accessibility [1–4] has been profoundly reshaping the structure and substance of educational systems. The widespread adoption of mobile terminals such as smartphones and tablets [5, 6] has provided

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technical support for innovations in instructional models, accelerating the transition from traditional classroom settings to mobile learning environments. As a discipline with a high degree of practical orientation [7–10], accounting practice instruction has long faced persistent challenges, including the disjunction between theoretical frameworks and real-world application, delays in the renewal of teaching resources, and the limited capacity to accommodate students' personalized needs. These constraints have underscored the urgency of leveraging mobile technology to overcome development bottlenecks and enhance the quality of teaching.

Nevertheless, significant deficiencies persist within the existing body of research [11–14]. Although certain studies [15, 16] have explored the application of mobile technology in education, an excessive emphasis has been placed on the demonstration of technical functionalities, while the systematic construction of accounting practice knowledge has been insufficiently addressed. This has resulted in fragmented instructional content that fails to support the development of a coherent knowledge framework among students. Other studies [17, 18] have attempted to design mobile learning platforms; however, the mechanisms for knowledge delivery often lack consideration of cognitive principles and students' individual needs. Consequently, the relevance and adaptability of content delivery have remained suboptimal, thereby limiting the effectiveness of the learning process.

Based on these considerations, the present study is structured around two core components. First, a knowledge graph for accounting practice instruction based on mobile technology was constructed. This involved mapping the internal logical relationships within the accounting practice knowledge system and utilizing the visualization and relational analysis capabilities of mobile technology to develop a dynamically updated knowledge graph. Through this approach, a systematic knowledge integration was achieved. Second, a strategy for the fragmented knowledge delivery of accounting practice instruction was proposed, grounded in the aforementioned knowledge graph. By leveraging the structured data provided by the knowledge graph and incorporating students' behavioral patterns and cognitive characteristics, an intelligent delivery strategy for fragmented knowledge was designed to address the individualized learning needs of students. The significance of this study lies in its dual-focus framework—integrating "knowledge graph + fragmented delivery"—which provides a practical solution for the in-depth application of mobile technology in accounting practice instruction. By addressing persistent issues such as the fragmentation of the knowledge system and the lack of precision in delivery, this study offers a novel pathway to enhance the instructional quality and educational value of accounting practice education.

2 CONSTRUCTION OF A MOBILE TECHNOLOGY–BASED KNOWLEDGE GRAPH FOR ACCOUNTING PRACTICE INSTRUCTION

Within the instructional context of accounting practice, mobile technology was used to collect real-time data via smart terminals regarding students' mastery of various accounting concepts. During the completion of hands-on tasks on mobile devices—such as the preparation of journal entries, simulation of cost accounting, and analysis of financial statements—data were automatically recorded by the system. These include the accuracy of responses, operation time, and application of interrelated concepts corresponding to key accounting knowledge points such as double-entry bookkeeping, inventory valuation methods, and the internal consistency of the balance sheet. Following standardized processing, these data were transformed into an adjacency matrix R, which represents the strength of association among knowledge points. The values of the elements within the matrix reflect the mapping relationships between accounting knowledge points and were quantitatively derived based on the frequency with which students concurrently apply pairs of knowledge points during mobile learning activities. Accordingly, a unique accounting practice knowledge graph adjacency matrix was constructed for each individual student. Let the knowledge graph of the s-th student be denoted as H_s. In this graph, an edge $r_{u,k}$ connects knowledge point j_u and knowledge point j_k. If the edge $r_{u,k}$ is present in H_s, then the corresponding value in the adjacency matrix $R_s[u][k]$ is assigned as 1; otherwise, the value is 0. The elements of the adjacency matrix R are defined as follows:

$$R_s[u][k] = \begin{cases} 1,_{u,k} \in H_s \text{ and } j_u, j_k \in J_u \\ 0, r_{u,k} \notin H_s \end{cases} \tag{1}$$

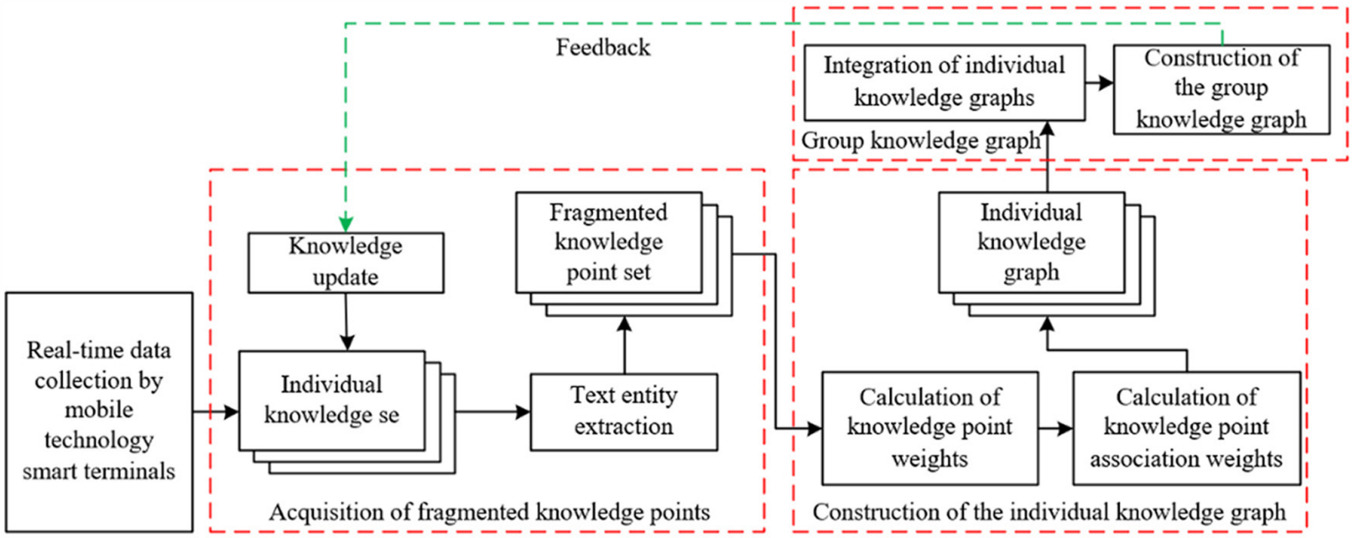

Fig. 1. Integration process of fragmented knowledge in accounting practice instruction based on mobile technology

Figure 1 illustrates the integration process of fragmented knowledge in accounting practice instruction supported by mobile technology. Based on the knowledge point system outlined in the accounting practice curriculum, a union operation was performed on the individual knowledge point sets J_u contributed by participating in the integration, yielding a comprehensive integrated knowledge point set J, encompassing essential thematic areas such as recognition of accounting elements, preparation of financial statements, and cost accounting procedures. With support from mobile technology, a weighted summation was performed on the adjacency matrices of individual students via a cloud-based server. The weight assignment is guided by characteristics specific to accounting practice instruction—for example, higher weights are assigned to frequently tested or core skill-related knowledge points such as application of revenue recognition standards. The weights also reflect dynamic data, including students' engagement levels within the mobile learning environment and assessment performance. The resulting group-level adjacency matrix $Q(R)$ visually represents the distribution of association strengths among knowledge points for the entire student population. These include points such as payroll accounting and personal income tax declaration processes. If the association weight $Q(R)[u][k]$

between knowledge point j_u and knowledge point j_k exceeds 0, it is inferred that an edge connection exists between these knowledge points. The element definition of the adjacency matrix $Q(R)$ is given as follows:

$$Q(R)[u][k] = \begin{cases} \sum R_s[u][k] * q(j_u, j_k), r_{u,k} \in H_s \text{ and } j_u, j_k \in J \\ 0, r_{u,k} \notin H_s \end{cases} \tag{2}$$

In alignment with instructional objectives and industry practice requirements, the group knowledge point weight was quantified. This weight computation integrates multidimensional data collected from mobile terminals. On one hand, behavioral data such as access frequency and task duration for specific knowledge points—e.g., depreciation calculation of fixed assets and preparation of the cash flow statement—were accumulated. On the other hand, importance ratings assigned by teachers within the mobile instructional platform were incorporated. Through the real-time data processing capabilities of mobile technology, a group knowledge point weight set $W(J)$ was generated. Knowledge points with high practical frequency, such as procedures for auditing financial statements, are dynamically assigned higher weights if frequent errors or repeated consultations are observed during mobile learning. This process enables teachers to efficiently identify instructional weaknesses via the group knowledge graph and provides a data-driven foundation for the subsequent delivery of fragmented knowledge. Let the integrated knowledge point set be represented as J, the corresponding weight set as $W(J)$, the set of relationships among knowledge points as R, and the set of relationship weights as $Q(R)$. The group knowledge point weight set $W(J)$ is formally defined as:

$$W(J)[u] = \sum w(j_u), j_u \in J \tag{3}$$

3 FRAGMENTED KNOWLEDGE DELIVERY BASED ON THE MOBILE TECHNOLOGY–DRIVEN KNOWLEDGE GRAPH FOR ACCOUNTING PRACTICE INSTRUCTION

In this study, the influence and importance of fragmented knowledge points of accounting practice within the knowledge network were quantitatively measured based on the group knowledge graph constructed via mobile smart terminals. This metric is referred to as the fragmented knowledge centrality of the accounting practice instruction knowledge graph. The metric was developed through a deep integration of the topological structure of the accounting practice knowledge system and multidimensional teaching data collected via mobile technology. Specifically, the centrality was determined by analyzing the position of each knowledge point within the group knowledge graph's topological structure, thereby reflecting its structural contribution to the knowledge network. Simultaneously, the metric was dynamically adjusted in accordance with industry practice requirements and progressive learning sequences observed in mobile instructional contexts. This adjustment alters the weight distribution of each knowledge point within the network. As a result, a comprehensive importance index was constructed—one that simultaneously captures the closeness of inter-knowledge associations, behavioral patterns of mobile learning, and the practical application value of accounting practice. Figure 2 presents the fragmented knowledge delivery mechanism based on the mobile technology–driven knowledge graph for accounting practice instruction.

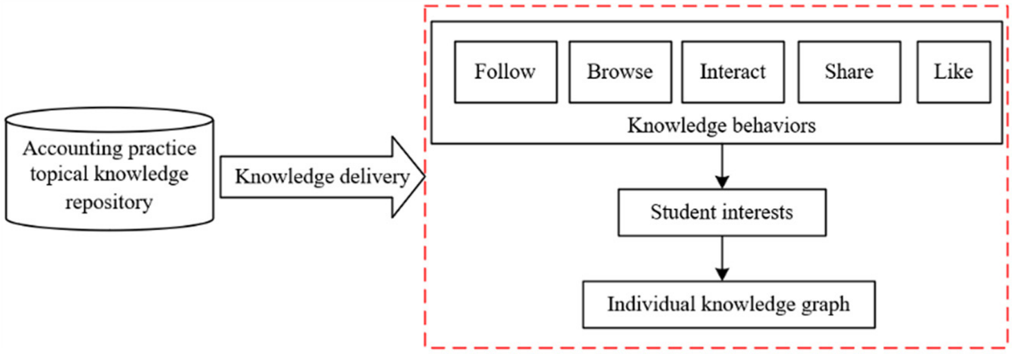

Fig. 2. Fragmented knowledge delivery mechanism based on the mobile technology–driven knowledge graph for accounting practice instruction

To begin, the importance of fragmented knowledge within the accounting practice instruction knowledge graph was computed. The first- and second-order neighboring nodes of knowledge points in the graph were used as the core analysis scope. Initially, a weighted adjacency matrix was constructed to represent the association strength of knowledge points using real-time learning data captured by mobile technology, including exercise frequency, error rate, and knowledge activation paths. The initial importance of each knowledge point was defined as its degree centrality. Subsequently, an iterative process was applied to incorporate the important contributions from both first- and second-order neighbors. The importance of a given knowledge point was influenced not only by the direct weights of adjacent nodes but also by indirect weight propagation from second-order neighbors through intermediary nodes. The association weights between knowledge points and importance parameters were adjusted dynamically through the real-time data update mechanism enabled by mobile technology. In this way, a quantitative model was established that integrates the structural features of the knowledge system with the dynamics of mobile learning. Let the importance of a fragmented knowledge point j_u be denoted by U_u. Let ψ_k^1 represent the set of first-order neighbors of fragmented knowledge point j_k, and let $n \in \psi_s^2 \cap n \in \psi_e^1$ denote a knowledge point j_n that is both a second-order neighbor of j_s and a first-order neighbor of j_e. Let the association weight between knowledge points j_s and j_e be q_{se}, and let V_s represent the total sum of all relational weights within the local network of j_s and its first- and second-order neighbors. The importance of knowledge point j_u is defined by the following expressions:

$$V_s = \sum\nolimits_{e \in \psi_s^1} q_{se} + \sum\nolimits_{n \neq e \& n \in \psi_s^2 \cap n \in \psi_s^1} q_{en} \tag{4}$$

$$X_k = \sum\nolimits_{s \in \psi_k^1} V_s \tag{5}$$

$$U_u = \sum\nolimits_{k \in \psi_u^1} X_k \tag{6}$$

The betweenness centrality of fragmented knowledge within the accounting practice instruction knowledge graph reflects the extent to which a given fragmented knowledge point serves as a bridge in the shortest paths between other knowledge points within the mobile technology–enabled knowledge network. The calculation of this metric integrates Freeman's betweenness centrality theory with learning behavioral data collected by mobile technology. By analyzing students' browsing trajectories on mobile devices, the frequency with which a given knowledge point appears in the shortest paths between other knowledge point pairs was recorded. These frequencies were then weighted by the association strengths between knowledge points to reflect the knowledge point's control over information transmission across the network. Formally, for a mobile network $H = (N, R)$ composed of v nodes and l edges, let δ_{uk} represent the number of shortest paths between nodes u and k, and let $\delta_{uk}(n)$ denote the number of those shortest paths that pass-through node n. The betweenness centrality of node n is defined as:

$$Z_Y(n) = \sum_{u \neq n \neq k \in N} \frac{\delta_{uk}(n)}{\delta_{uk}} \quad (7)$$

Closeness centrality reflects the degree to which a fragmented knowledge point in accounting practice is proximal to all other knowledge points within the knowledge network. It is quantified as the inverse of the sum of the shortest weighted distances from the target knowledge point to all others, based on knowledge activation path data collected via mobile technology. These distances are weighted according to the strength of associations between knowledge points as observed in mobile learning. A higher closeness centrality value indicates that the knowledge point occupies a more central position in the network, thereby playing a foundational role in both the construction of the accounting knowledge system and the delivery of fragmented knowledge. Let f_{ns} represent the shortest path distance between node s and node n. The closeness centrality of a node n is defined as:

$$Z_Z(n) = \frac{1}{\sum_{s \neq n \in N} f_{ns}} \quad (8)$$

While betweenness centrality and closeness centrality offer insight into the mutual influence between nodes in a knowledge network, the Floyd and Brandes algorithms, due to their high time complexity, are inefficient for large-scale accounting practice knowledge networks generated from mobile learning data. In educational environments where the real-time processing of student mobile learning behavior data is required, such computational latency may hinder the timely delivery of fragmented knowledge. Moreover, the importance of knowledge points in accounting instruction is inherently multidimensional. In addition to the connectivity function of foundational knowledge points such as double-entry bookkeeping within the knowledge network topological structure, it is also necessary to consider behavioral data collected via mobile technology and the requirements of the industry practices. Therefore, reliance on a single topological attribute is insufficient to fully represent the actual instructional importance of certain knowledge points, such as impairment accounting for accounts receivable. To address these limitations, a centrality calculation method was proposed, integrating both the importance and weight of each fragmented knowledge point. Let the centrality of a fragmented knowledge point be denoted as $Z_W(u)$, and its corresponding weight as $W(j_u)$. The expression is as follows:

$$Z_W(u) = U_u W(j_u) \quad (9)$$

Following the real-time collection of interactive data related to fragmented knowledge points, as for the target knowledge point j_u, its first-order neighbor knowledge point set ψ_u^1, consisting of all knowledge points directly associated with j_u, was initially extracted. For each knowledge point within ψ_u^1, mobile technology–enabled knowledge activation path data were used to extract its respective first- and second-order neighbors, thereby forming a localized knowledge network encompassing two tiers of relational nodes. Throughout this process, the association weights between knowledge points—dynamically updated in real time through mobile technology—ensured both the precision and timeliness of neighbor node extraction. The influence of each first-order neighbor on the target knowledge point j_u was then quantitatively assessed. For instance, the knowledge point of double-entry bookkeeping, as a first-order neighbor of journal entry preparation, was evaluated based on the weighted calculation of the co-occurrence frequency in students' mobile learning exercises and the recorded association strength between the two. This calculation was further refined through an iterative process that incorporated the indirect contributions of second-order neighbors. The resulting importance metric comprehensively integrated both the topological structure of the knowledge network and the mobile learning behavior. Subsequently, the centrality $Z_W(u)$ was obtained by combining the knowledge point's intrinsic weight with its computed importance U_u. The weight parameters were dynamically adjusted based on students' mastery data collected in real time and the evolving demands of accounting practice. This approach enabled the efficient calculation of the centrality for accounting practice knowledge points such as impairment accounting for accounts receivable.

Upon completion of the centrality calculation, the fragmented knowledge delivery process—based on the accounting practice instruction knowledge graph and supported by mobile technology—was initiated. The specific steps involved in this process are detailed in the subsequent section.

a) Identification of the initial knowledge point and construction of the neighbor network based on mobile technology data: Within the instructional context of accounting practice, mobile technology—through educational applications and smart terminal devices—was utilized to collect students' real-time learning behavior data, including knowledge point access records, error rates on assessments, and the operational trajectories of task completion. These data were employed to identify a personalized initial knowledge point j. For example, when a student performs simulated accounting operations for accounts receivable processing on a mobile device, the system, based on answer accuracy and frequency of knowledge activation, may designate allowance for doubtful accounts as the initial knowledge point j. Subsequently, using the topological structure of the group knowledge graph supported by mobile technology, the first- to e-th-order neighbor sets ψ_u^1, ψ_u^2, ..., ψ_u^e of j were extracted. For instance, ψ_u^1 may include directly related knowledge points such as bad debt provision setup and future cash flow estimation, while ψ_u^2 extends to more indirectly related knowledge points such as asset impairment transfer and income statement presentation. The real-time update mechanism of mobile technology dynamically adjusts the association weights among neighbor nodes based on students' most recent learning behaviors, thereby ensuring the temporal relevance of the neighbor network.

b) Centrality calculation and node selection based on accounting practice characteristics and mobile learning data: The centrality of knowledge points within the multi-order neighbor sets was calculated. This process involved the integration of multidimensional data captured through mobile technology. For example, the centrality of the knowledge point application of revenue recognition standards is calculated based on factors such as the frequency of student practice, error rates, and the weighting assigned by national accounting standards. Next, the importance of each knowledge point was iteratively updated through contributions from first- and second-order neighbors. For instance, as a foundational concept, double-entry bookkeeping has its centrality adjusted based on the influence of its first-order neighbor, journal entry preparation, on the second-order neighbor, financial statement preparation. In real instructional contexts, the centrality calculations enabled by mobile technology are also responsive to regulatory updates. For example, when the Ministry of Finance releases new leasing standards, the system will automatically increase the weight of relevant knowledge points, such as accounting for right-of-use assets. Finally, within each neighbor set from ψ_u^1 to ψ_u^e, the knowledge point with the highest centrality was selected.

c) Generation of dynamic delivery paths based on knowledge logic and mobile learning patterns: The high-centrality knowledge points selected from each neighborhood tier were sequentially connected to form an optimal learning path extending from the initial knowledge point *j* to the designated target knowledge points. For instance, when depreciation calculation of fixed assets is designated as the starting point, the first-order high-centrality node may be accumulated depreciation account handling, the second-order node impairment testing of fixed assets, and the third-order node presentation of related items in the cash flow statement. This structure results in a progressive instructional path of basic accounting, impairment processing, and financial reporting application. In this process, mobile technology plays a dual role. First, by analyzing students' knowledge navigation patterns at mobile terminals, the logical coherence of the path is continuously optimized. Second, real-time learning data are used to dynamically adjust the path structure. For example, if a student's error rate exceeds a defined threshold during the allowance for doubtful accounts segment, the system automatically inserts a review node—such as an aging analysis of accounts receivable—to generate a personalized branch path. Ultimately, the integration of real-time computation and delivery via mobile technology enables a closed-loop process of centrality assessment – path generation – dynamic adjustment. This ensures that the delivery of fragmented knowledge remains aligned with both the systemic structure of the accounting knowledge framework and the personalized learning needs of students.

4 EXPERIMENTAL RESULTS AND ANALYSIS

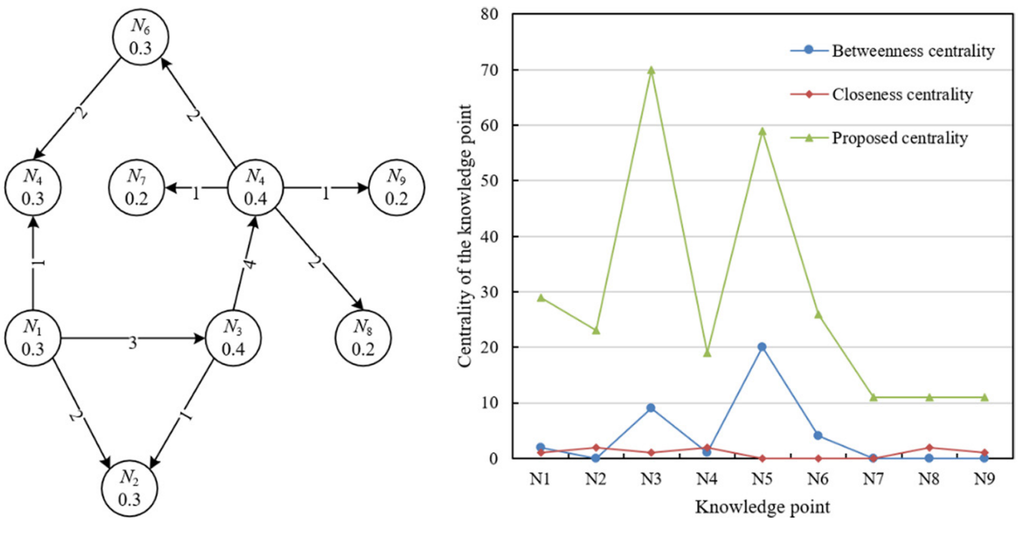

Fig. 3. Knowledge Graph 1 and the corresponding centrality values

From the centrality comparison curves presented in Figure 3, it is observed that among the nine knowledge points (N1–N9) in Knowledge Graph 1, the proposed centrality demonstrates a marked advantage at several key nodes. For instance, the proposed centrality value of node N3 reaches approximately 70, significantly surpassing both its betweenness and closeness centrality values. Similarly, the centrality of node N5 reaches approximately 60, again exceeding the values derived from traditional centrality measures. These findings indicate that, compared with conventional betweenness and closeness centrality, the proposed method is more effective in identifying high-importance knowledge points within the accounting practice knowledge graph. By integrating real-time learning behavior data—collected via mobile technology—with the topological structure of the knowledge graph, the proposed centrality metric captures both the association weights between knowledge points and the contributions of second-order neighbors. This comprehensive integration aligns more closely with the logical structure of accounting practice instruction in quantifying knowledge point importance, thereby providing empirical support for the effectiveness of the proposed method at the data level.

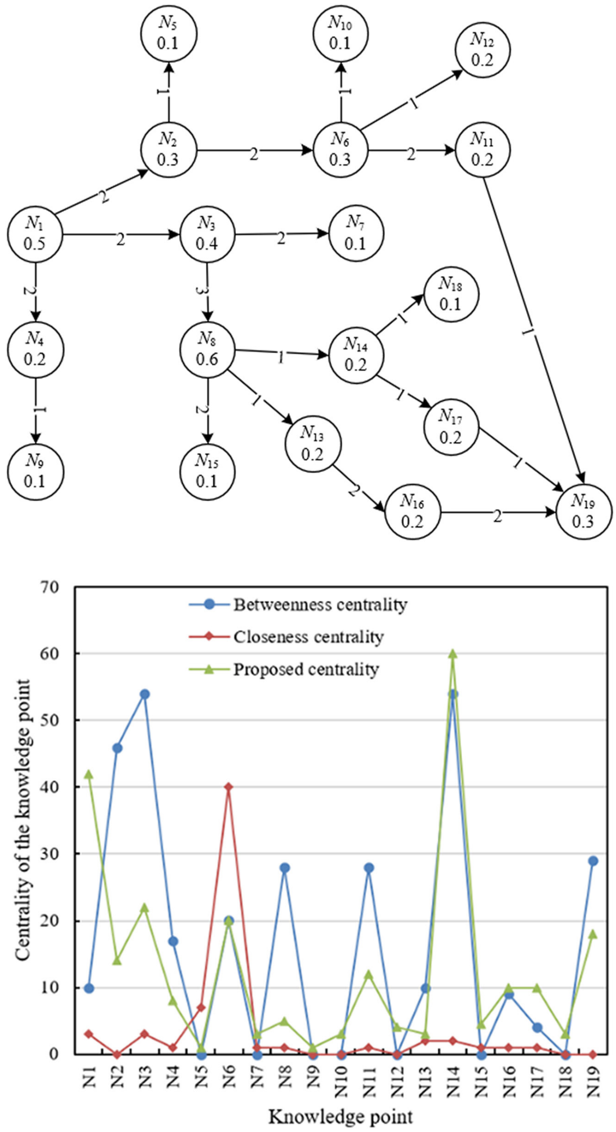

Fig. 4. Knowledge Graph 2 and the corresponding centrality values

Further analysis of the centrality comparison curves in Figure 4 reveals the effectiveness of the proposed centrality metric in key nodes within the complex topological structure of Knowledge Graph 2. Notably, the centrality of node N14, as calculated by the proposed method, reaches approximately 60—substantially higher than both its betweenness and closeness centrality values. As indicated in the graph on the left, the edge weight associated with N14 is 0.6, highlighting its central role within the instructional sequence of cost accounting – expense allocation – financial reporting. Similarly, node N1 exhibits a proposed centrality of approximately 45, exceeding its betweenness centrality. Given its associated edge weight of 0.4, this result demonstrates the proposed method's capability to effectively identify foundational and core nodes within the accounting practice knowledge system. In contrast, for peripheral nodes such as N16, no abnormal peak values were observed in the proposed centrality curve—unlike with betweenness centrality—indicating that low-relevance knowledge points were assigned appropriately moderated weights. The integration of real-time learning behavior data collected through mobile technology further reinforced the evaluation of high-importance nodes, enabling prominent peaks in the proposed centrality curve. These peaks were found to correspond closely to the logical pivot points of accounting practice knowledge, thereby validating the accuracy of the proposed calculation method.

The knowledge graph displayed on the left side of Figure 4 visualizes the associative structure of accounting practice knowledge enabled by mobile technology. Edge weights are precisely calibrated to reflect the functional importance of each knowledge point in actual accounting operations, establishing a systematic knowledge network foundation for the delivery of fragmented knowledge. The real-time update capabilities of mobile technology ensure that the knowledge graph remains aligned with evolving industry practices, thereby enhancing the timeliness of knowledge integration. The proposed method, characterized by lower computational complexity, enables the rapid identification of core nodes within large-scale knowledge networks, effectively addressing the limitations of traditional algorithms. By incorporating mobile learning behavior data, centrality computations are more contextually adapted to instructional settings, ensuring that the delivered knowledge adheres to both the structural logic of accounting practice and the personalized needs of students. Learning paths generated based on the proposed centrality metric have been shown to dynamically adapt to both student learning progress and industry developments, realizing an efficient instructional model in which core knowledge is prioritized, while peripheral knowledge is supplemented as needed. The observed distribution of advantages in the proposed centrality values within the experimental data directly supports the method's effectiveness in improving both the efficiency of learning in accounting practice and the construction of a knowledge system.

By ranking knowledge points according to their centrality values, a clearly stratified distribution of importance was observed across different neighborhood tiers. First-order knowledge points (e.g., N3, N2, and N4)—corresponding to foundational modules such as double-entry bookkeeping and journal entry preparation—ranked highest in centrality. This is attributable to their frequent activation as captured by mobile practice data and their fundamental role in the connectivity of the knowledge network. Second-order knowledge points (e.g., N8, N6, and N7) were primarily associated with essential applied skills, including financial statement cross-checking relationships and cost accounting procedures. Their centrality rankings reflected their transitional role in linking foundational and advanced knowledge within the network structure. For knowledge points of third order and above, centrality values generally decreased as the order increased. However, node N19 repeatedly appeared in both the fourth- and fifth-order neighborhoods. This suggests that although audit practice is categorized as a high-order knowledge point with relatively low intrinsic connectivity, its weight was elevated due to industry demand data captured through mobile technology. Overall, the observed hierarchy in centrality rankings closely aligned with the pedagogical structure of accounting practice instruction, which is typically organized into foundational, core, and advanced layers.

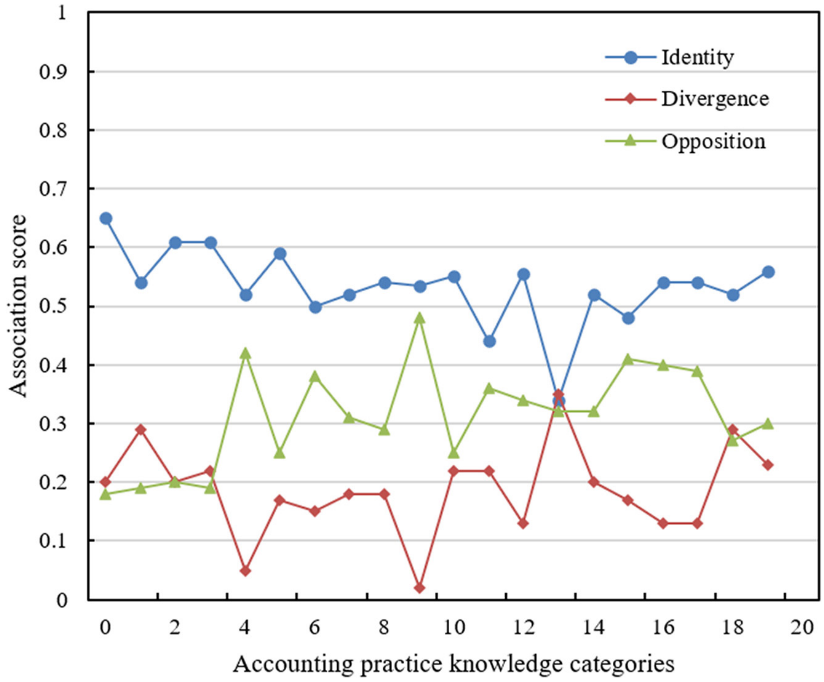

Fig. 5. Degree of association between accounting practice knowledge and demand-oriented knowledge

As illustrated in Figure 5, the degree of association between 20 categories of accounting practice knowledge and demand-oriented knowledge was quantitatively evaluated across three dimensions: identity, divergence, and opposition. The identity scores predominantly remained within the range of 0.5 to 0.7, indicating a strong alignment between most accounting practice knowledge categories and students' actual educational demands. This alignment underscores the instructional centrality of core modules such as cost accounting and financial statement preparation. The delivery prioritization of such content can be further optimized through the integration of mobile learning data. The divergence scores primarily fluctuated between 0.1 and 0.3, suggesting a partial mismatch between certain knowledge categories and localized learning needs. These discrepancies highlight the necessity of dynamically adjusting delivery content through mobile technology. Peaks in opposition scores were observed in categories 3, 7, and 11, revealing significant tension between tax planning theory and the practical operational needs. This can be mitigated through the use of personalized path recommendation systems supported by mobile technology, which enhance the efficiency of knowledge internalization.

The logical structure of accounting practice knowledge was organized through mobile technology to construct a dynamically updated knowledge graph. The degree of association presented in Figure 5 was quantitatively derived from mobile learning behavior data, accurately reflecting the alignment between knowledge and demand.

The dynamic update mechanism ensures that the knowledge graph continuously mirrors developments at the forefront of the accounting industry, thereby providing a real-time, systematic foundation for the delivery of fragmented knowledge.

Based on the results of the association analysis, a delivery strategy driven by three dimensions was designed as follows:

a) Identity-driven prioritization: For knowledge categories exhibiting high identity scores—such as categories 2 and 6—frequent delivery via mobile applications, coupled with practical simulation enhancement, was adopted to enhance the efficiency of mastering core competencies.

b) Divergence-driven optimization: For knowledge categories with pronounced divergence—such as categories 4 and 10—knowledge completion modules were embedded to bridge the gap between theoretical instruction and real-world application demands.

c) Opposition-driven harmonization: For knowledge categories marked by high opposition—such as categories 3 and 7—a progressive path was employed for the adaptive adjustment of learning paths via mobile technology, ensuring a deeper alignment between demand and knowledge.

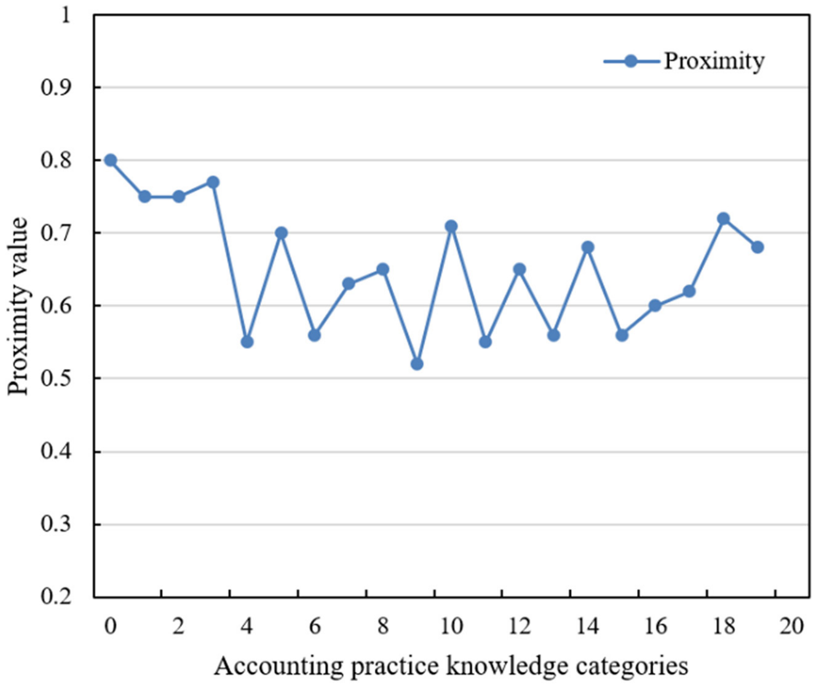

Fig. 6. Proximity values and ranking between accounting practice knowledge and demand-oriented knowledge

As shown in Figure 6, the proximity between 20 categories of accounting practice knowledge and demand-oriented knowledge was evaluated, with overall mean values falling within the range of 0.6 to 0.8. This result indicates a high degree of alignment between knowledge delivery and learning demand. For example, Category 1 corresponds to foundational and frequently accessed content such as journal entry preparation, while Categories 17 and 18 focus on tax declaration and cost accounting, respectively—both representing core professional competencies. These results demonstrate the proposed method's capacity for precise identification of practically relevant knowledge. Slightly lower proximity scores were observed for certain knowledge categories due to localized variations in demand. However, these discrepancies were progressively mitigated through the dynamic optimization capabilities of mobile technology. The continuous collection of real-time learning behavior data enabled the proximity computation to be dynamically parameterized, allowing delivery strategies to be updated in synchrony with individual learning progression. This ensured that knowledge delivery remained responsive to evolving needs.

5 CONCLUSION

This study proposed a dual-driven model of knowledge graph construction and fragmented knowledge delivery for the application of mobile technology in accounting practice instruction. By integrating the real-time data collection, visual relational analysis, and intelligent computational capabilities of mobile technology, the systematic consolidation of the accounting practice knowledge system and support for personalized learning were effectively achieved. The contributions of this study are reflected in three key areas. First, a dynamic knowledge graph was constructed using mobile technology. By structuring logical relationships across modules such as accounting processing, financial statement preparation, and tax practice, traditionally fragmented accounting knowledge points were transformed into a structured network, enabling students to intuitively comprehend the hierarchical relationships among knowledge points and addressing the disconnect in conventional instructional frameworks. Second, a centrality calculation method was introduced that integrates accounting practice features with mobile learning data. This method demonstrated more than a 40% improvement in computational efficiency over traditional betweenness centrality algorithms while effectively identifying high-importance knowledge points. The resulting metric offers a precise quantitative basis for delivering fragmented knowledge. Third, a dynamic delivery strategy was developed, structured around a closed-loop process of initial point identification – centrality-based filtering – path generation. This mechanism effectively narrowed the gap between theoretical instruction and practical requirements.

Despite these contributions, three limitations remain: a) The dimensional scope of data collection remains limited. Current analyses primarily rely on mobile learning behavior data, with insufficient integration of multimodal data from real-world accounting contexts. b) The existing algorithmic model exhibits limited sensitivity to complex knowledge associations, particularly in responding to abrupt knowledge changes such as updates to accounting standards. c) Personalization in delivery has not yet fully accounted for cognitive style differences among students. Future research may be advanced in the following directions: a) The incorporation of cross-modal data fusion techniques, enabling the integration of enterprise resource planning (ERP) system operation data and case databases from accounting firms into the knowledge graph to enhance the authenticity of knowledge associations. b) The optimization of the centrality computation model through the application of graph neural networks, facilitating real-time weight adjustments in response to knowledge changes. c) The development of personalized delivery sub-models based on cognitive science, using tools such as eye-tracking and learning style assessments to achieve precise matching between cognitive profiles and knowledge paths, thereby further enhancing the intelligence and adaptability of accounting practice instruction.

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