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PAPER

Exploring Pathways for Mobile Interaction Technologies to Foster Innovation in Entrepreneurial Education Models

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ABSTRACT

With the rapid advancement of information technology, mobile interaction technologies have emerged as a pivotal force driving educational innovation, especially in the realm of entrepreneurial education. These technologies have not only transformed the methods of acquiring and sharing knowledge but have also facilitated interaction and collaboration among learners. This investigation aims to explore how mobile interaction technologies can foster innovation in entrepreneurial education models. The focus is specifically placed on the construction of a mobile interaction-based collaborative learning team environment model oriented towards knowledge building as well as on identifying collaborative strategies that can effectively enhance entrepreneurial learning teams based on mobile localized influence networks. It has been discovered that optimizing mobile learning environments and collaborative strategies improves the quality of interaction and learning outcomes among teams, providing new pathways for entrepreneurial education. Existing research, however, lacks a comprehensive discussion on the deep integration of mobile interaction technologies with entrepreneurial education, especially in terms of systematic studies on team collaboration and the process of knowledge construction. Through theoretical exploration and empirical analysis, this manuscript aims to bridge the research gap, providing theoretical and practical support for innovation in entrepreneurial education models. This endeavor holds significant research value and practical implications.

KEYWORDS

mobile interaction technology, entrepreneurial education, team collaboration, knowledge construction, collaborative strategy, mobile learning environment

1 INTRODUCTION

In the contemporary era marked by the swift evolution of information technology, mobile interaction technologies have deeply permeated various facets of daily life and work, exerting a particularly notable impact on educational models [1, 2]. With the widespread adoption of smartphones and tablets, mobile learning, as an

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innovative form of learning, has provided learners with significant convenience in terms of time and space [3–5]. Especially in the field of entrepreneurial education, the utilization of mobile interaction technologies enhances knowledge acquisition and sharing and also fosters interaction and collaboration among learners, thereby creating new opportunities for innovation in entrepreneurial education models.

Entrepreneurial education, which plays a crucial role in nurturing talent with innovation and entrepreneurial capabilities, has seen significant model innovation that greatly enhances learners' practical skills and innovative thinking [6, 7]. Through their unique modes of interaction and learning environments, mobile interaction technologies are capable of effectively fostering deep learning of knowledge and efficient collaboration among teams, which is particularly vital for entrepreneurial education [8–11]. However, the effective integration of mobile interaction technologies with entrepreneurial education to promote innovation in educational models remains a topic worthy of in-depth exploration.

Although there has been some progress in the application of mobile interaction technologies in the field of education, research focusing on the innovation of entrepreneurial education models is relatively scarce and lacks depth. Most existing studies focus on the technological aspects of mobile technologies and case analyses of their applications, with a lack of systematic research on the fundamental needs of entrepreneurial education and its integration with mobile interaction technologies [12–14]. Particularly in the process of team collaboration and knowledge construction, designing effective mobile learning environments and collaborative strategies to support entrepreneurial learning calls for further empirical research and theoretical exploration [15–17].

This study aims to address the aforementioned research gaps by constructing a mobile interaction-based collaborative learning team environment model oriented towards knowledge construction. It also aims to identify effective collaborative strategies within entrepreneurial learning teams based on mobile localized influence networks. The first section explores the construction of mobile interaction environments that support the knowledge construction of entrepreneurial learning teams. It focuses on analyzing interaction modes and knowledge-sharing mechanisms during team collaboration. The second section focuses on exploring effective collaborative strategies for entrepreneurial learning teams using mobile localized influence networks. The goal is to enhance interaction and improve learning outcomes for teams. Through these research endeavors, this study not only enriches the theoretical application of mobile interaction technologies in the field of entrepreneurial education but also provides new perspectives and strategies for entrepreneurial education practice, holding significant research value and practical implications.

2 CONSTRUCTION OF A MOBILE INTERACTION ENTREPRENEURIAL LEARNING TEAM COLLABORATION ENVIRONMENT MODEL ORIENTED TOWARDS KNOWLEDGE CONSTRUCTION

In the realm of entrepreneurial education, facilitating learners to achieve higher levels of knowledge construction is identified as a core objective. The introduction of mobile interaction technologies has provided new momentum and possibilities for realizing this goal. Consequently, a model for constructing a mobile interaction-based collaborative learning team environment oriented towards knowledge construction is proposed. This model aims to leverage the characteristics of mobile interaction technologies, such as the ability to access information anytime and anywhere, real-time communication and interaction, as well as personalized learning experiences, to promote and optimize the collaboration and co-construction of knowledge among entrepreneurial learning teams. Compared to traditional online collaborative learning environments, this model particularly emphasizes the utilization of mobile technologies to facilitate field research, market analysis, and entrepreneurial practice activities. Furthermore, it explores how these technologies can support deep thinking and knowledge exchange among team members, thereby more effectively meeting the requirements for fostering innovative thinking and teamwork capabilities in entrepreneurial education.

Figure 1 presents the framework of the main system model. In the mobile interaction entrepreneurial learning team collaboration environment model, learning scenarios are set against the backdrop of entrepreneurial projects, market research, or real-world business issues, providing specific entrepreneurial situations and objectives. These scenarios stimulate learners' focus on crucial business concepts and skills by incorporating the portability and immediacy of mobile interaction technologies. It enables learners to apply acquired knowledge in real or simulated business environments, such as conducting market research or interacting with potential customers through mobile devices. This inspires active learning and encourages the practical application of theoretical knowledge.

The learning community within this model consists of learners interested in entrepreneurship or business innovation, instructors providing guidance, industry experts, and potential investors. Utilizing mobile interaction technologies, this learning community can engage in real-time communication and collaboration through social media platforms, mobile discussion groups, and video conferences, enhancing interactivity and connectivity among members. Such a design enables learners to communicate and collaborate with peers or mentors at any time and place, jointly solve problems, and co-construct knowledge systems. This facilitates deep knowledge construction and the development of entrepreneurial thinking.

In this model, learning activities are structured as a series of tasks and challenges focused on entrepreneurial projects. These activities include writing business plans, conducting market analysis, and designing and testing product prototypes. These activities leverage the capabilities of mobile interaction technologies, such as conducting field research with mobile devices, utilizing professional software applications for data analysis, or employing virtual reality tools for product design. Task-based learning activities not only help learners deeply understand business concepts and skills in practice but also, with the support of mobile technologies, enable a more flexible and personalized learning experience, increasing interaction and cooperation among learners.

Learning analytics also play a crucial role in this model. The collection and analysis of data on learners' interactions, progress, and outcomes in the mobile environment provide educators and teams with profound insights into learning effectiveness and team collaboration status. Utilizing data analysis tools and techniques can help educators and team members understand their learning strengths and weaknesses and adjust learning strategies and collaboration methods, thereby optimizing the entire entrepreneurial learning process. Through continuous learning analytics, teams can effectively construct knowledge while optimizing collaboration efficiency and strategies, propelling entrepreneurial education to higher levels.

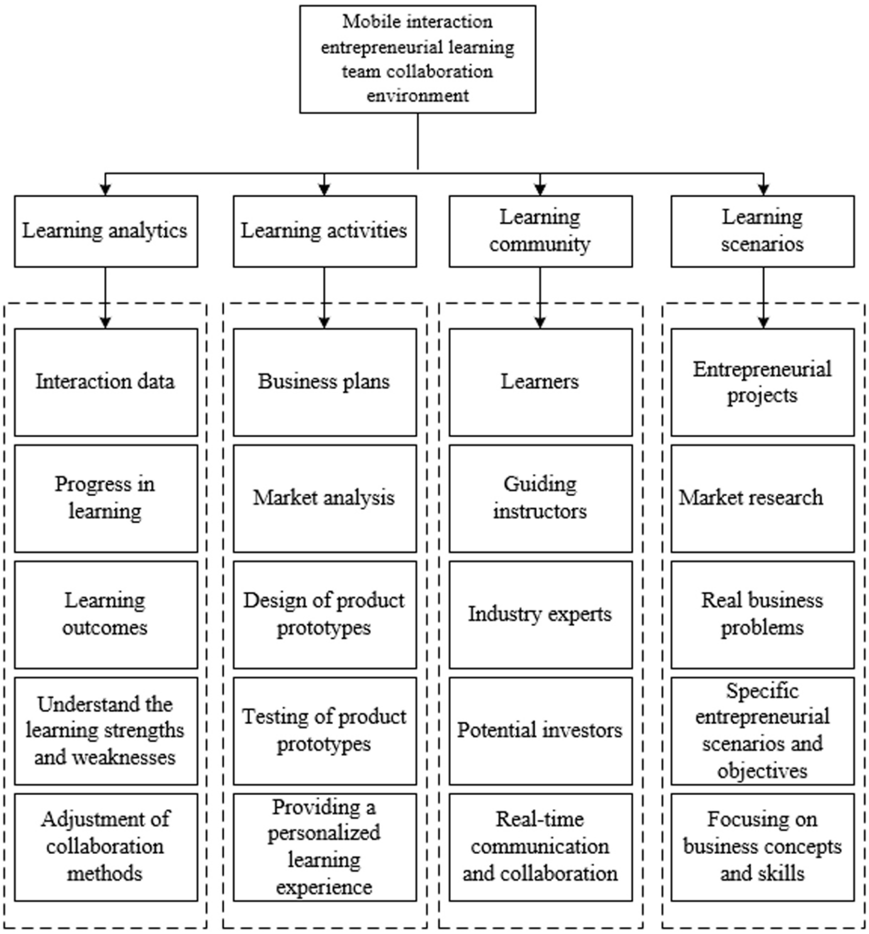

Fig. 1. Main system framework of the model

3 EXPLORING ENTREPRENEURIAL LEARNING TEAM COLLABORATION STRATEGIES THROUGH MOBILE LOCAL INFLUENCE NETWORKS

This study is dedicated to exploring the application of mobile local influence networks within the field of entrepreneurial education, with the goal of discovering collaboration strategies for entrepreneurial learning teams. The effectiveness and network characteristics of these strategies are analyzed and validated through three key modules, which are detailed below.

Module for constructing local influence subgraphs of target entrepreneurial team members: Within the collaborative environment of entrepreneurial learning teams, this module initially establishes a global network graph reflecting the collaboration and interaction among team members, including internal team members, guiding instructors, and industry advisors, based on mobile interaction data such as instant messages, shared files, and discussion threads. This network graph is constructed to capture both direct and indirect collaboration relationships among team members. Subsequently, local influence subgraphs of target entrepreneurial team members are extracted based on various selection criteria, such as member activity level, professional skill relevance, and contribution to entrepreneurial projects. This process provides a precise data foundation for in-depth analysis.

Module for validating the effectiveness of local influence subgraphs: This module focuses on validating the effectiveness of collaboration strategies discovered in real entrepreneurial education and team activities. It utilizes advanced graph neural network technology to integrate information on individual contributions and inter-team collaboration relationships by deeply encoding nodes and edges within the local influence subgraphs. During this process, members' mobile interaction data is semantically encoded using models such as bidirectional encoder representation from transformers (BERT) and combined with edge information from collaboration strategies. Finally, the network model evaluates the influence and effectiveness of collaboration strategies, ensuring that the proposed strategies enhance team efficiency and innovation capacity in actual entrepreneurial projects.

Module for analyzing complex network characteristics: This module approaches the analysis of local influence subgraphs within entrepreneurial learning teams from statistical and network science perspectives. It focuses on the structural stability of the collaboration network, the efficiency of information flow, and the dynamic evolution of strategies. By examining interaction patterns, collaboration intensity, and centrality metrics among team members, we can uncover the underlying network mechanisms of effective collaboration strategies. Moreover, the study examines changes in collaboration strategies across different periods. It analyzes the impact of strategy adjustments on team innovation capability and project progression speed, offering scientific recommendations for strategic optimization in entrepreneurial education.

3.1 Extraction of mobile local influence subgraphs

The principle of extracting local influence subgraphs in this study is to reveal the complex and close interaction patterns and collaboration strategies among members of the entrepreneurial team. This study examines the unique use of mobile interaction technologies in entrepreneurial education, emphasizing the exchange of interaction data among team members via mobile communication and social platforms. Initially, the extraction of local influence subgraphs based on propagation path length considers the patterns of information flow and influence within the entrepreneurial team. Following the principle of "three degrees of influence" in social networks, direct communications among team members are regarded as strong connections, having a direct impact on entrepreneurial activities and decisions, while indirect communications are viewed as weak connections, primarily used for information transfer. In this process, we analyze the interaction path lengths between target entrepreneurial team members and other members. We select 1-hop and 2-hop neighbor subgraphs to examine both direct and indirect collaboration relationships and their impact on the effectiveness of team collaboration strategies.

Subsequently, a provenance analysis of the entrepreneurial team, focusing on key entrepreneurial team members, is conducted. An "entrepreneurial team" refers to a group of individuals who have close collaborative relationships in entrepreneurial projects. This analysis employs two strategies: one is based on relevance importance provenance, i.e., identifying the core collaboration group most closely related to target entrepreneurial team members by analyzing the intensity and frequency of interactions within the team; the other is through depth-first search provenance, exploring the entire team collaboration path under the maximum path length limit. This method aims to obtain local influence subgraphs that include all key interaction nodes and connection paths to reveal the full picture of information flow and influence transmission. Finally, these extracted local influence subgraphs not only reflect the internal collaboration dynamics and information dissemination patterns of the entrepreneurial team but also enable a thorough analysis of the structural characteristics of nodes and edges within these subgraphs, offering insights into the underlying mechanisms and potential issues of team collaboration.

3.2 Determining the effectiveness of mobile local influence subgraphs

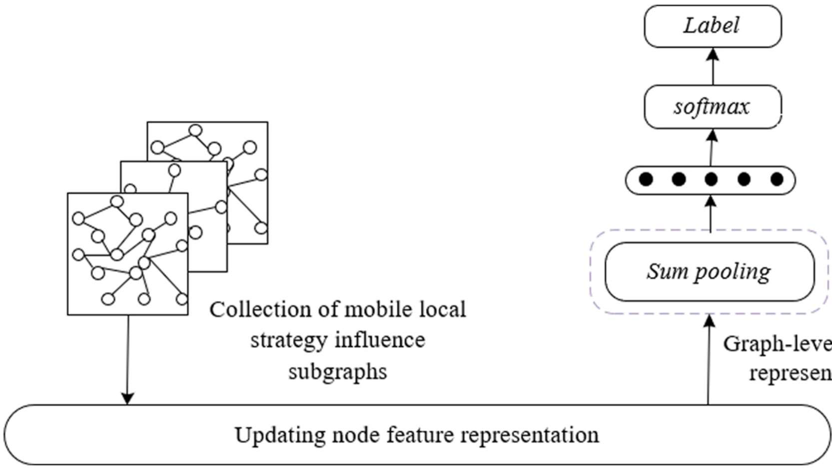

Fig. 2. Classification framework for mobile local influence subgraphs

In this study, the primary rationale for utilizing a graph isomorphism network (GIN) to model both the semantic and structural similarities among members within entrepreneurial teams is rooted in the understanding that the collaborative dynamics within entrepreneurial teams are evident not only in direct interactions like communication and discussions among members but also in the overall structure of the team's interaction network. This approach enables researchers to deeply understand and capture the subtle collaboration patterns among team members and their impact on the overall performance of the team. This helps in identifying key factors that promote or hinder entrepreneurial success. The GIN model effectively aggregates the characteristics of team members and their relationships. Through iterative updates, it simulates the Weisfeiler-Lehman test to identify structurally similar subgraphs. This ensures that when extracting features of local influence subgraphs, both the individual characteristics of nodes and their positions and roles within the team network are comprehensively considered. Figure 2 illustrates the classification framework for mobile local influence subgraphs. Figure 3 illustrates the process of updating node feature representations. Specifically, based on the different layers of encoded information, it is divided into node-level encoding and graph-level encoding. Assuming the set of whole graph node feature vectors at layer m is represented by $G^{(1)}$, the feature vector of the node to be updated at layer m is denoted by g_n^m, the feature vector of the neighbor node at layer m is denoted by g_i^m, and the corresponding edge feature is denoted by r_{ni}.

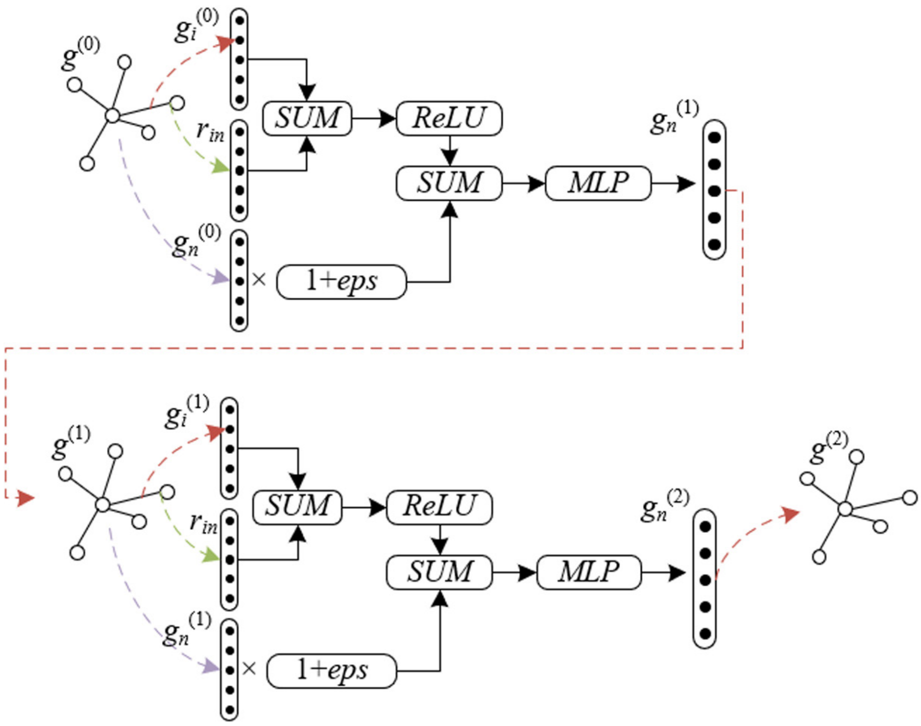

Fig. 3. Process for updating node feature representation

The principle of node-level encoding focuses on deeply capturing the individual behavioral characteristics of team members and their mutual collaboration relationships, facilitating the understanding and optimization of team collaboration patterns. During this process, semantic features of team members are initially extracted from mobile interaction data. The BERT model is utilized to convert interactions, such as messages and discussions, into initial feature vectors for nodes. This ensures that the deep semantics of text data are effectively captured. For collaborative relationships among members, collaboration behaviors in the interaction data, such as task allocation and resource sharing, are analyzed and represented using one-hot encoding to illustrate various types of collaboration strategies. If there are multiple collaboration relationships among members, the corresponding strategy features are represented by the summation of one-hot encoding vectors. This approach preserves the diversity of strategies while facilitating subsequent processing. Subsequently, through the designed node and edge feature encoding layers, these discrete features are uniformly mapped to the same semantic space. This mapping considers each member and their collaborative relationships' features through a message-passing mechanism, achieving a comprehensive encoding of the team's internal complex interaction patterns. Assuming the feature vector of the current node is represented by $g_n^{(m-1)}$, the set of neighbor nodes for n is represented by $V(n)$, the feature vector for a neighbor node is denoted by $g_i^{(m-1)}$, and the corresponding edge feature vector is denoted by $r_{in}^{(m-1)}$, with the hyperparameter represented by γ^m, the following equation characterizes the process of updating information for edges and node features at each layer of the graph isomorphism network.

$$g_n^m = MLP^m\left((1+\gamma^m)g_n^{(m-1)} + \sum_{i \in V(n)} \mathrm{ReLU}(g_i^{(m-1)} + r_{in}^{(m-1)})\right) \tag{1}$$

Assuming the number of layers in the GIN is represented by M, the following equation provides the calculation formula from node information to whole graph information in graph-level encoding.

$$g_H = AV\left(\sum g_n^{(M)}\right) \tag{2}$$

3.3 Analysis of complex network characteristics

The core principle of analyzing complex network characteristics lies in the thorough exploration of the dynamic interaction patterns among members within entrepreneurial teams and their evolving characteristics over time. This analysis focuses not only on the direct and indirect interactions of team members during different time periods but also aims to reveal how these interactions influence the formation and change of collaboration strategies, as well as their contribution to the overall performance and influence of the team. By dividing the data captured through mobile interaction technologies by months, the study meticulously examines the evolution of internal interactions within the team over time. The aim is to capture the commonalities of explicit and implicit strategies within the entrepreneurial team collaboration network and their changing patterns over time. This dynamic analysis enables researchers to identify crucial collaboration patterns at various stages of the entrepreneurial team's development. It helps assess their influence on the team's innovation capacity and project success rate, offering detailed insights and strategic recommendations for entrepreneurial education and team management grounded in temporal and spatial dynamics. Figure 4 presents a schematic of the dynamic nature of social networks.

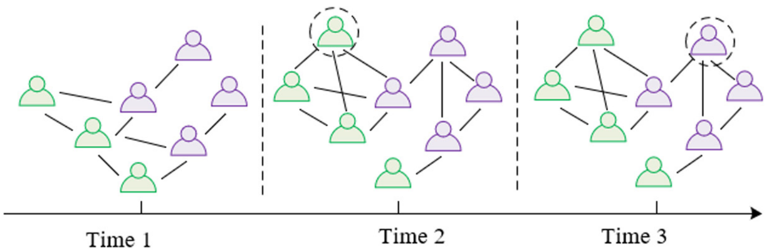

Fig. 4. Schematic of the dynamic nature of social networks

This study first conducts an analysis of direct and indirect interactions, aiming to clearly distinguish and understand the influence of direct interactions, such as face-to-face meetings and instant messaging communication, versus indirect interactions, such as information or influence passed through a third party involved in joint work, among members within entrepreneurial teams. Based on mobile interaction data, such as call records, message exchanges, and social media interactions, this analysis evaluates and quantifies the frequency, intensity, and depth of direct interactions, as well as the role of indirect interactions in information transmission and influence diffusion. Assuming the number of interaction strategy edges in the subgraph is represented by v_{ST}, and the number of all entrepreneurial team members in the subgraph is represented by v_{US}, with the number of 1-hop neighbor interaction edges and j-hop neighbor interaction edges represented by r_{1HO} and r_{JH}, respectively, the following calculations are made:

$$o_{IN} = \frac{r_{JH}}{v_{ST}} \tag{3}$$

$$o_{IN} = \frac{r_{JH}}{v_{ST}} (k \geq 2) \tag{4}$$

The computational principles for analyzing entrepreneurial teams and their collaboration strategies aim to reveal the dynamic distribution of different roles and collaboration strategies within entrepreneurial teams and their interactions. By analyzing mobile interaction data, such as communication records and social media interactions, the study first identifies key internal roles such as leaders, mediators, and executors, along with their proportions within the local influence subgraphs. It then delves into how these roles influence the team's overall performance and innovation capacity through various collaboration strategies, such as information sharing, resource allocation, and task coordination. Assuming the number of entrepreneurial team members of type M in the subgraph is denoted by v_{US_u}, the following formula calculates the proportion of different roles of entrepreneurial team members within the local influence subgraphs:

$$o_{RE_u} = \frac{v_{US_u}}{v_{US}} (u \in RT, LT, NF) \tag{5}$$

Assuming the number of users of type M in the subgraph is denoted by v_{US_u}, the following formula calculates the proportion of actions by different roles of entrepreneurial team members within the local influence subgraphs relative to the total actions.

$$o_{BE_u} = \frac{r_{US_u}}{v_{ST}} (u \in RT, LT, NF) \tag{6}$$

Assuming the number of edges related to common themes in the subgraph is denoted by v_{CO}, the following formula calculates the number and proportion of edges related to common themes:

$$o_{CO} = \frac{v_{CO}}{v_{ST}} \tag{7}$$

Assuming the number of edges related to mentions among entrepreneurial team members within the subgraph is denoted by v_{CM}, the following formula calculates the number and proportion of mentioned collaboration strategies within the entrepreneurial team:

$$o_{CM} = \frac{v_{CM}}{v_{ST}} \tag{8}$$

The computational principle for analyzing global importance and influence aims to explore the implicit strategies between entrepreneurial teams and the general mobile network user community, as well as their potential impact on the entrepreneurial process and outcomes. This analysis utilizes mobile interaction data, such as social media interactions and instant messaging records, to track and quantify the behaviors of information mention and dissemination among entrepreneurial teams, between entrepreneurial teams and the general mobile network users, as well as among the general mobile network users themselves. Specifically, assuming the number of edges related to mentions among ordinary entrepreneurial team members within the subgraph is denoted by v_{UM}, the following formula calculates the number and proportion of mentioned collaboration strategies within the entrepreneurial team.

$$o_{UM} = \frac{v_{UM}}{v_{ST}} \tag{9}$$

Assuming the number of edges related to mentions between the general mobile network user community and entrepreneurial teams within the subgraph is denoted by v_{UC}, the following formula calculates the collaboration strategies mentioned and their proportion between the general mobile network user community and entrepreneurial teams:

$$o_{UC} = \frac{v_{UC}}{v_{ST}} \tag{10}$$

Finally, assuming the number of significant entrepreneurial team members within the subgraph is denoted by v_{IM}, the following formula calculates the proportion of significant entrepreneurial team members:

$$o_{IM} = \frac{v_{IM}}{v_{US}} \tag{11}$$

4 EXPERIMENTAL RESULTS AND ANALYSIS

It is observed from Table 1 that the mean values of multiple components showed improvement in the second round compared to the first, particularly in aspects like mobile social platform support (from 3.12 to 4.98), actual problem-solving skill development (from 2.89 to 4.12), instant messaging tool utilization (from 3.15 to 4.25), real-time communication mechanism (from 3.25 to 4.25), and deep collaboration platform (from 3.36 to 4.25), demonstrating significant positive changes ($p < 0.05$ or $p < 0.01$). Participants perceived significant improvements in these dimensions. The significant enhancement in mobile social platform support ($p = 0.003$) emphasizes the crucial role of mobile social platforms in fostering team collaboration and knowledge sharing. The significant improvements in industry report analysis and actual problem-solving skill development ($p = 0.008$ and $p = 0.005$, respectively) underscore the effectiveness of the mobile interaction environment focused on knowledge construction in enhancing learners' analytical abilities and their capacity to solve real-world problems.

The experimental results suggest that the model for a mobile interaction entrepreneurial learning team collaboration environment, oriented towards knowledge construction, effectively facilitated interaction and knowledge sharing among learners. The significant increase in mean values and statistical significance underscores the important role of mobile interaction technology in supporting real-time communication, collaboration, creativity, collision, and enhancement of problem-solving abilities. The significant progress, especially in the support of mobile social platforms and the utilization of instant messaging tools, verifies that this model can provide an interactive and efficient learning environment for entrepreneurial education.

Table 2 and Figure 5 present a comparison of results for evaluating the effectiveness of mobile local influence subgraphs using various subgraph extraction methods. The evaluations are based on area under curve (AUC) values and Macro-F1 values. From the results, it is observed that the extraction method involving a 3-hop neighbor performs the best in terms of effectiveness, with an AUC value of 75.48% and a Macro-F1 value of 73.25%, significantly higher than other methods. In contrast, the method presented in this study has the lowest performance among four methods, with AUC and Macro-F1 values of 57.69% and 57.23%, respectively. This outcome suggests that a broader range of neighbors, such as 3-hop neighbors, can more accurately capture the potential influence and collaboration patterns among team members, considering the complex interactions and influence propagation within entrepreneurial teams. The method presented in this paper may have limitations in some aspects and may not fully utilize the information in the mobile local influence network. These experimental results are of significant importance for validating research methods for extracting entrepreneurial learning team collaboration strategies based on mobile local influence networks. Although the method presented in this paper does not demonstrate the best performance in the current effectiveness evaluation, the outstanding performance of the 3-hop neighbor extraction method highlights the potential and value of utilizing mobile local influence networks in entrepreneurial education. This further proves that exploring and utilizing the complex interactions among members of entrepreneurial teams is crucial for understanding and promoting team collaboration.

Table 1. Components of the mobile interaction entrepreneurial learning team collaboration environment oriented towards knowledge construction

Measurement Dimension	Mean ± SD		t	P
	Round 1 <n = 29>	Round 2 <n = 29>		
Actual business problem repository	4.12 ± 1.23	3.58 ± 1.24	0.521	0.612
Mobile learning resource access	4.12 ± 1.26	4.12 ± 1.35	–0.097	0.925
Market data integration	4.25 ± 1.36	3.58 ± 1.35	0.854	0.389
Industry report analysis	3.89 ± 1.23	3.78 ± 1.48	–2.63	0.008**
Real-time news updates	3.26 ± 1.26	4.25 ± 1.32	–0.521	0.612
Active exploration mechanism of learners	3.15 ± 1.58	4.25 ± 0.92	–0.536	0.584
Actual problem-solving skill development	2.89 ± 1.36	4.12 ± 1.25	–2.895	0.005**
Mobile social platform support	3.12 ± 1.36	4.98 ± 1.87	–3.125	0.003**
Instant messaging tool utilization	3.15 ± 1.56	4.25 ± 1.32	–2.236	0.022*
Collaboration software application	4.12 ± 1.25	3.87 ± 1.25	–0.51	0.612
Real-time communication mechanism	3.25 ± 1.24	4.25 ± 1.25	–2.451	0.014*
Deep collaboration platform	3.36 ± 1.15	4.25 ± 1.25	–2.352	0.022*
Creative collision space	3.58 ± 1.35	4.25 ± 0.85	0.289	0.042*
Experience exchange forum	4.21 ± 1.56	4.25 ± 1.21	–0.915	0.789
Virtual entrepreneurial challenge design	3.87 ± 1.45	4.25 ± 4.23	–0.387	0.345
Mobile research task arrangement	3.89 ± 1.54	3.89 ± 1.35	–0.915	0.715
Online mind mapping tool	3.98 ± 1.25	4.25 ± 1.24	0.051	0.356
Interaction in real business environments	3.54 ± 1.58	4.35 ± 1.14	–0.312	0.947
Learning process data collection	3.58 ± 1.58	3.98 ± 1.32	–0.289	0.754
Personalized learning feedback system	4.26 ± 1.36	4.23 ± 1.04	0.215	0.759

Notes: *means $p < 0.05$, and **means $p < 0.01$.

Table 2. Comparison of results for determining the effectiveness of mobile local influence subgraphs using different subgraph extraction methods

Subgraph Extraction Method	AUC Value (%)	Macro-F1 Value (%)
1-hop neighbor	71.23	67.98
2-hop neighbor	62.58	63.21
3-hop neighbor	75.48	73.25
Method presented in this study	57.69	57.23

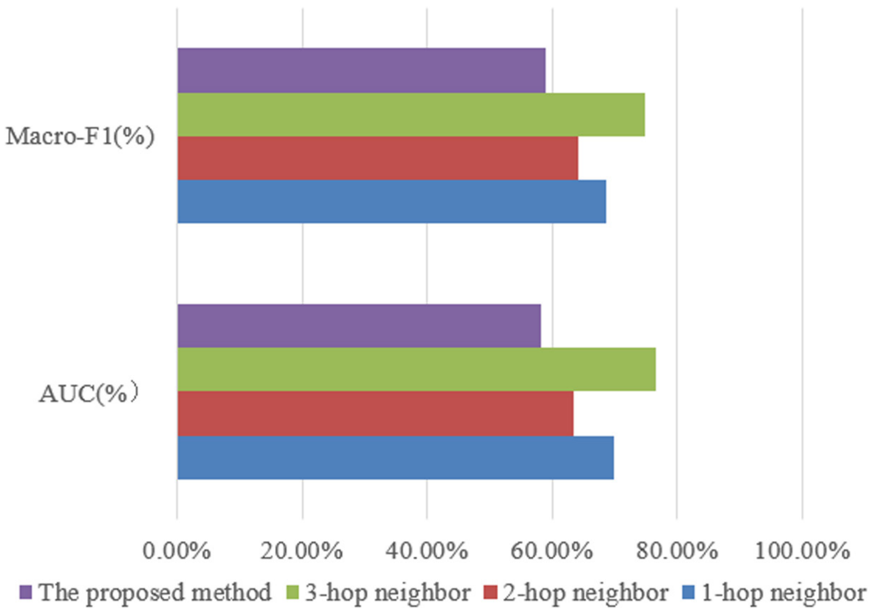

Fig. 5. Comparison of results for determining the effectiveness of mobile local influence subgraphs using different methods

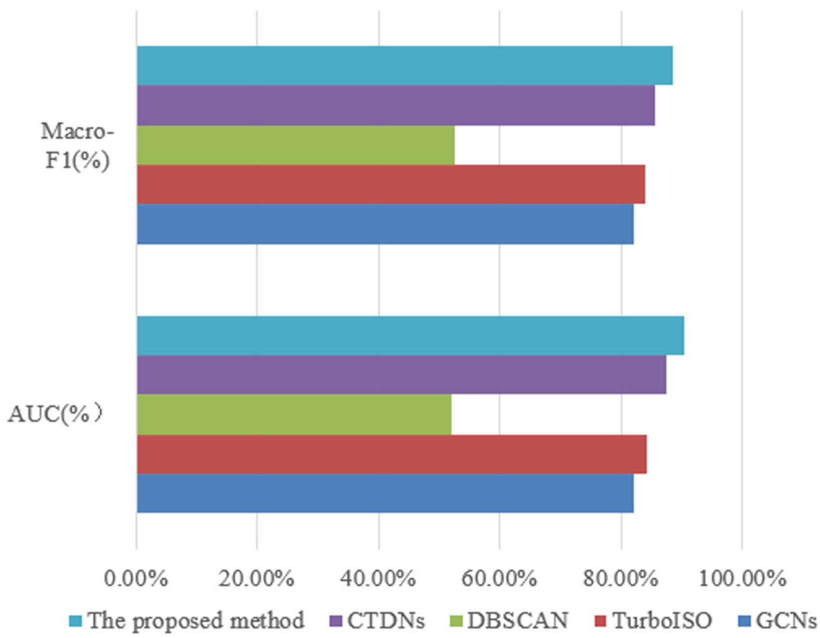

Fig. 6. Comparison of results for mobile local influence subgraph extraction using different methods

Figure 6 presents the comparison results of AUC values and Macro-F1 values for different methods in the task of extracting mobile local influence subgraphs. The data reveals that the method presented in this paper performs optimally among all compared methods, achieving an AUC value of 90.36% and a Macro-F1 value of 88.63%, which are notably higher than other methods such as graph convolutional networks (GCNs), TurboISO algorithm, density-based spatial clustering of applications with noise (DBSCAN), and continuous time dynamic networks (CTDNs). especially when compared to CTDNs, which also performed excellently with an AUC value of 87.44% and a Macro-F1 value of 85.59%, the method introduced in this study still demonstrates higher effectiveness. This outcome substantiates the superior performance of the method discussed in this study in handling mobile local influence network data, especially in extracting and analyzing entrepreneurial learning team collaboration strategies.

These experimental results underscore the effectiveness of the research on extracting entrepreneurial learning team collaboration strategies based on mobile local influence networks. By comprehensively considering the complexity of mobile local influence networks and employing advanced analytical techniques, the method presented in this study not only successfully unearthed effective entrepreneurial learning team collaboration strategies but also surpassed several other popular network analysis methods in effectiveness evaluation. This achievement not only confirms the potential application of mobile local influence networks in the field of entrepreneurial education but also provides new perspectives and tools for future research aimed at exploring and optimizing the collaboration and knowledge-sharing mechanisms of entrepreneurial learning teams.

5 CONCLUSION

This study constructs a model for an interaction entrepreneurial learning team collaboration environment model oriented towards knowledge construction. It explores the collaboration strategies of entrepreneurial learning teams based on mobile local influence networks with the aim of offering theoretical and practical support for innovating entrepreneurial education models. The study content is divided into two main parts. Firstly, it explores how to construct a mobile interaction environment that supports the knowledge construction of entrepreneurial learning teams. This part focuses on analyzing interaction patterns and knowledge-sharing mechanisms during team collaboration. Secondly, it is dedicated to mining effective entrepreneurial learning team collaboration strategies by analyzing mobile local influence networks to optimize interaction and learning effectiveness among teams. The experimental results showcase the depth and breadth of this study through the analysis of component elements, t-test analysis of self-assessment scales, determination of the effectiveness of mobile local influence subgraphs, and comparison of results from different subgraph extraction methods.

In conclusion, the research methods and results of this study underscore the practical value of mobile interaction technology in entrepreneurial education across various levels. Especially in facilitating knowledge sharing within entrepreneurial learning teams, enhancing interaction efficiency, and optimizing collaboration strategies, significant effects have been demonstrated. This study not only proposes an effective mobile interaction environment model oriented towards knowledge construction but also verifies the effectiveness of the method for mining collaboration strategies based on mobile local influence networks through empirical analysis.

This provides a new pathway for optimizing interaction and collaboration for entrepreneurial learning teams.

However, the study also has certain limitations. For instance, the performance of the method presented in this study is not always optimal in some experimental settings. Moreover, the study primarily focuses on the construction and validation of models and strategies, which may necessitate further exploration of the universality and adaptability of these models and strategies in various entrepreneurial education contexts. Future research directions could include: i) expanding and refining the mobile interaction entrepreneurial learning environment model to suit a wider range of educational and business scenarios; ii) exploring more data-driven methods to mine and analyze the collaboration dynamics of entrepreneurial teams; and iii) delving into the application effects of mobile local influence networks in different cultural and geographical backgrounds.

6 ACKNOWLEDGMENT

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