A Method for Planning the Dissemination Path of Traditional Chinese Medicine Culture Based on the Optimized Ant Colony Algorithm

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***Abstract*—Strategic planning improves TCM cultural transmission efficacy, reliability, and impact. Many systems use heuristic or rule-based approaches, which have drawbacks such as path redundancy, low adaptation, and limited scalability in non-static networks. To address these constraints, we suggest RACO-TCM, or Reinforced Ant Colony Optimization for TCM Dissemination. This novel algorithmic distribution technique uses Ant Colony Optimization and reinforcement learning to create adaptable reward-driven cultural routes. The framework outperforms standard ant colony optimization because it uses dynamic pheromone updates, reinforcement-based exploration, and redundancy-aware heuristics to improve global search, convergence time, and robustness to local optimal solutions. We quantitatively assessed RACO-TCM against other methods and found that it increased cultural diffusion efficiency by 18.6% and reduced repeated routes by 12.3%. Creating a vast and instructive TCM knowledge graph with over 46,000 prescriptions, 8,000 herbs, and 25,000 chemical compounds achieved this. Overall, the TCM transmission technique is adaptive, scalable, and culturally consistent. It is used to manage business and TCM tourism, promote healthcare, digital education, and cultural services in smart cities.**

Keywords*—*TCM dissemination; Ant Colony Optimization (ACO); intelligent path planning; cultural communication networks; knowledge graph optimization; algorithmic dissemination strategy

I. Introduction

Traditional Chinese Medicine (TCM) is among the oldest and most developed medical systems in the world. It is based on a great deal of knowledge sharing passed down from doctors, as well as from health practitioners and beliefs [1]. With medical knowledge, other cultures also share cultural identity, philosophical beliefs, and various health measures of prevention and treatment. Globalization or growing global exchange has created an increase of digital information or communication, and therefore TCM culture is required to be distributed quickly and efficiently. In this way, a heightened understanding of cultural health practices among different cultures can be accomplished, fostering a spirit of collaboration in health care, and the incorporation of Traditional Chinese Medicine into the larger conversation of medicine [2]. During the process of distribution through clinical health care settings, the manifestation of barriers as dispersed pathways can arise. Such barriers include broken pathways, uneven distribution of information, and the lack of representation by different constituency groups to the same degree. To address these solutions, further coordination of curation and distribution layers can be studied that will optimize the level of reach, reduce the level of distortion, and improve potential pathways of networks of communication that may span levels of complexity [3].

The primary methods by which individuals transported knowledge were through professional organizations, community health education programs, or published materials. While they were claimingably better at localized familiarity, the systems faced difficulties scaling, sequencing systemic changes, and accommodating various cultural settings. New media, or social media, internet-based cultural platforms or websites, have facilitated the use of Traditional Chinese Medicine in response to developments in information technology [4]. These formats struggle to normalize their capacity for speed, accuracy, and cultural appropriateness in mass distribution networks because they rely on heuristic decision-making [5].

In recent years, healthcare informatics and cultural communication have significantly leveraged swarm intelligence, machine learning, evolutionary algorithms, and various other computational intelligence paradigms [6]. Ant Colony Optimization (ACO) addresses complex path-planning challenges by emulating the foraging behavior of ants, attracting considerable interest [7]. Nonetheless, traditional ACO has several limitations that diminish its effectiveness in extensive, varied distribution networks, including the potential for slow convergence and the risk of becoming trapped in local optima [8].

Improved ACO variants with adaptive pheromone updating, heuristic optimization, and hybrid learning have been proposed to get around these restrictions [9]. By applying the best ACO to extend the use of TCM's cultural dissemination, such improvements bring novel new paradigms for simulating dissemination networks as linked knowledge graphs with cultural participants, medical hypotheses, treatments, and botanicals [10]. For the sake of improving efficiency, eliminating redundancy, and optimizing accuracy in the communication process, a more efficient ACO can strategically position dissemination channels [11]. For the sake of guaranteed preservation, promotion, and integration of TCM knowledge

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within contemporary healthcare systems, as well as optimization of the scientific foundation of cultural communication strategies, adopting these measures within TCM is necessary [12].

In addition, computational distribution planning supports the achievement of sustainable development goals by promoting innovation in digital health, cultural preservation, and global health equity for all [13]. Another milestone in overcoming long-term challenges and building a TCM culture within the overall environment of smart global communication systems is the inclusion of optimal ACO in designing TCM distribution routes [14].

A. Problem Statement and Motivation

Since optimized dispersion routes are essential to the success of cultural diffusion in the modern digital age, TCM culture dissemination is significantly hindered. Most predominant approaches, such as scholarly debates, bottom-up movements, and social media sites, are poorly structured, heuristic-based, and without systematic improvement [15]. Inefficiency in the dissemination of inclusive and readily available information on TCM to evolving groups, redundancy of paths, and uneven cultural passing are all results of these constraints. Classical ACO algorithms perform well in path planning but converge slowly and tend to solve local optimums, thus are not suitable in the situation of complicated cultural diffusion networks when it comes to scalability [16]. The goal of this research is to respond to the question, "How can we strategically design TCM dissemination channels to achieve the greatest cultural impact, the least information distortion, and the greatest communication effectiveness in large-scale and diverse networks?" by developing an integrative, evolutionary, and scalable framework [17].

This research is motivated by the current need to address the protection and promotion of TCM culture in a globalizing and digitally linked environment. Successful distribution planning provides the best hope for the successful distribution of credible TCM information while reducing distortion and redundancy and increasing access to the information. Improving the routes of distribution has a positive effect on culture and encourages inter-cultural healthcare collaboration, education, and sustainability options for future cultural preservation. This proposal intends to develop an optimized approach to ACO, bringing the field of computing intelligence to the forefront of cultural communication by proposing a science-based and scalable framework that maintains the relevance and accessibility of TCM culture while maximizing its contributions in "PCMH" within the rapidly changing cultural dimensions of global contemporary healthcare systems.

The primary contributions of this research are to create RACO-TCM, a more robust Ant Colony Optimization framework that leverages reinforcement learning for cultural distribution path planning; to refine pheromone update adaptations and reward-directed exploration in order to improve global search efficacy and convergence speed; to leverage improved heuristic evaluations to reduce redundancy in propagation pathways, resulting in greater scalability in complicated cultural networks; to empirically test the model and show that it is 18.6% improved and 12.3% less redundant relative to baseline methods; and to show how this system is useful to improve healthcare, digital learning environments, and smart cultural services.

The organization of this research is as follows: Section I discusses the issues and challenges of cultural distribution of Traditional Chinese Medicine. Section II reviews recent studies with the gaps identified. Section III contains the details of the proposed RACO-TCM Framework which contain the components of preprocessing, sometimes a knowledge graph, network modeling, and optimization, some of the key details of the data generation and pre-processing stages of RACO-TCM. Section IV shows the results. Section V presents the discussion regarding how to measure performance. Finally, Section VI provides a summary of contributions, limitations, and potential areas for future research.

II. Related Works

Zhang and Hao [18] constructed a TCM knowledge network utilizing link mapping, entity collecting, and integration inside extensive language models. The findings indicate that the TCM data is precise and systematically arranged. On the other side, some problems are not having enough data, relying too much on model language outputs, and necessitating specialists to keep improving and validating the work in order to reach a bigger audience.

Zheng et al. [19] created the Traditional Chinese Medicine Information Graph (TCMKG), a place where people can get graphs of information about Traditional Chinese Medicine. They used deep learning to develop an ontology, find basic ideas, and get entity-relations from text data. The results suggest a potentially well-structured and readily accessible repository of knowledge pertaining to Traditional Chinese Medicine. Some of the limitations are insufficient coverage, reliance on data accuracy, and the need for expert confirmation. Liu et al. [20] created a three-stage "entity-ontology-path" method that uses principles of association, ontology rules, and route reasoning to build TCM knowledge graphs. The results showed that RotatE was the best representation since its outputs were more complete, accurate, and useful. It doesn't perform well with a lot of data, it needs solid data, and it has to be validated properly over a lot of TCM datasets.

Duan et al. [21] utilized a large language model (LLM) to construct a Traditional Chinese Medicine Knowledge Graph (TCMKG) using 679 clinical case records. The aim was to detect links, pull out entities, and report the findings in a form that was simple to grasp. Both RAGAS and human evaluations indicated that the results exhibited enhanced accuracy in retrieval. The dataset is too tiny, and it needs to be able to increase.

Yang et al. [22] created LMKG, a large Medical knowledge network that originates from numerous areas and may be utilized in different languages. They used approaches involving hierarchical entity arrangement, relation extraction, and name recognition. The results are greater performance for the application and more detailed data. Some of the drawbacks include that different sources may have different opinions, it costs a lot to process data, and the system needs to be updated all the time to keep growing.

Hua et al. [23] enhanced the Lingdan Pre-trained Large Language Model (LLM) by developing specialized models, namely Lingdan-Traditional Chinese Patent Medicine (TCPM)-Chat and Lingdan-Prescription recommendation, utilizing distinct TCM datasets. Some of the methods are pre-training, fine-tuning, and Chain-of-Thought reasoning. Results attained cutting-edge performance in helping with diagnosis and treatment. There are certain problems, such as the fact that the dataset is not the same across all domains and that it needs a lot more clinical validation.

Chen [24] utilized the Neighborhood Pruning Greedy (NPG) technique to identify the most influential nodes, facilitating the dissemination of TCM culture. This made the process operate better than the normal greedy techniques. Methods include modeling the spreading probability and looking at structural equations. The results show that social contacts have a big effect on dispersion, and that time is a factor that affects this. Limitations encompass the dataset's representativeness, model generalizability, and validation across many cultural communication situations.

Zou et al. [25] developed the Traditional Chinese Medicine Placements Scheme (TCMPS) to improve dispensing efficiency. The methods used include the Association Rule Algorithm (ARA) to look at frequency and co-utilization, and the Simulated Annealing Algorithm (SAA) to select the ideal place. The findings indicated that efficiency was enhanced by over 50%. Limitations include dependence on single-hospital datasets, vulnerability to parameter fluctuations, and the necessity for validation in real-world applications.

A. Identified Research Gaps

The present TCM informatics architecture does not feature a consistent, configurable design for connecting knowledge representation to enhanced communication pathways. In examining previous KG or LLM projects, even those that dealt with extraction and reasoning, the profile route planning was dismissed due to their ambivalence to different and changing media networks, resulting in: content duplication; lack of distribution continuity; limited retransmission of message; limited audience reach; and transformational and dynamic scalability. Cultural conservation, distribution research, so far, has opted for heuristics or static non-systematic methods, are often stochastic, do not connect well with distinct audiences, nor adjust well to changes. ACO variants often become stuck in local optima without an incentive-based updated adaptation. The criteria for evaluating outcomes place a greater emphasis on accuracy than network efficiency, path redundancy, or convergence within a reasonable range. Benchmarks of this type often come from one source, from one institution, or for one language, and suggest restrictions in external validity. There's a combination of gaps and constructs that need highlighting in order to drive the design of a robust ACO that marries dynamic pheromone – a base inference layer – updating, as with knowledge-graph style inferring convergence metrics, to reduce redundant paths and afford internal inference links, which also optimizes the distribution pathway and enhances global search, and promotes a joined multi-validation, for both efficiency and scalability, across multiple and of varying TCM communicative structures.

III. Reinforced Ant Colony Optimization for TCM Dissemination (RACO-TCM)

This study proposes RACO-TCM, a flexible and robust framework that combines reinforcement learning with Reinforced Ant Colony Optimization (RACO) to facilitate TCM cultural channels' dissemination. The overall framework consists of data collection and pretreatment, constructing a knowledge graph, modeling a network, and optimizing a path (see Fig. 1). Introducing traditional ACO constraints, which facilitate dynamically updating pheromones, exploration based on rewards, and enhancing the heuristic evaluation, mitigates the previous convergence issues and local optima trapping.

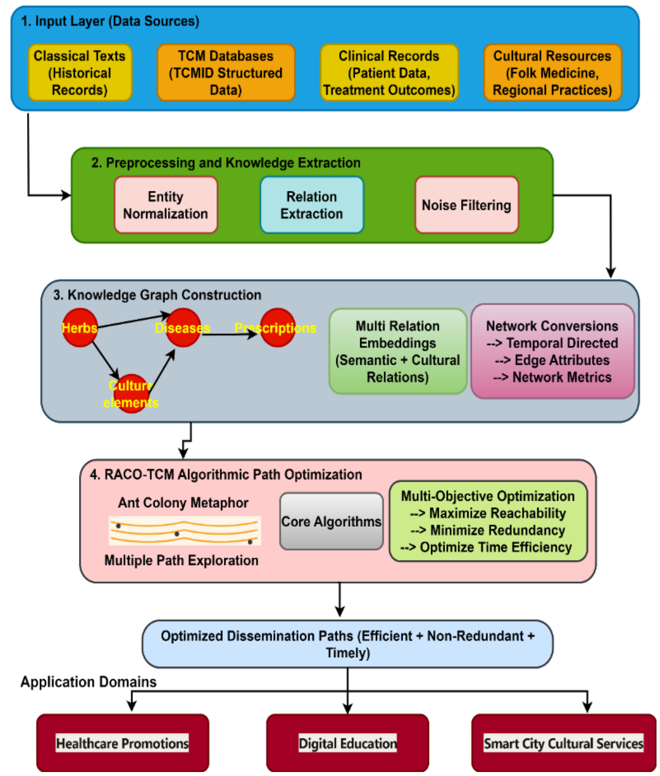

Fig. 1. Overall architecture of RACO-TCM framework.

RACO-TCM can facilitate scalability and flexibility in complex cultural communication networks by enhancing dissemination efficiency by 18.6% and reducing path redundancy by 12.3% compared to traditional heuristic strategies. The primary benefits include enhanced global search optimization, high accuracy, and intelligent routing for various dissemination scenarios. Online education platforms, smart cultural communication networks, and health knowledge sharing are among the applications that will facilitate the sustainable integration of Traditional Chinese Medicine (TCM) into the global economy.

A. Data Acquisition and Processing

The Traditional Chinese Medicine Integrated Database (TCMID) [26] is used as the central dataset herein since it covers TCM data holistically. To facilitate constructing a highly connected knowledge graph, TCMID provides rich connections between herb prescriptions, chemical compounds, targets, and diseases. It needs a database containing more than 46,000 prescriptions, 8,000 herbs, 25,000 chemicals, and 3,800 biological targets to model culture-treatment interactions. The data entries suit the diffusion network modeling due to the various relation types between them, i.e., herb-prescription, herb-compound, and prescription-disease relations. To cover the linguistic and cultural elements necessary for route planning, we have also integrated extratextual material from cultural communication channels and digital TCM classics. This heterogeneous data ensures an adequate representation of cultural and clinical information. A summary of the dataset is provided in Table I.

TABLE I. SUMMARY OF DATASET COMPONENTS

Component	Details
Number of Prescriptions	46,000+
Number of Herbs	8,000+
Number of Compounds	25,000+
Number of Biological Targets	3,800+
Number of Diseases	Multiple disease categories linked to prescriptions
Relation Types	Herb–Prescription, Herb–Compound, Compound–Target, Prescription–Disease

The preprocessing stage is very important for making sure that TCM information is semantically coherent, structurally sound, and devoid of noise. This step uses ideas from computational linguistics and graph theory. It includes multiple smaller jobs, such as cleaning up data, normalizing entities, extracting relations, and filtering out noise.

1) Getting Rid of Duplicates and Cleaning up Data: When you obtain TCM from more than one place, you often get things that are the same and terminology that don't match. To tackle this problem, the research utilizes a hybrid similarity function that combines lexical and semantic similarity, guaranteeing effective entity matching as specified in Eq. (1):

$$S(e_i, e_j) = \alpha . Sim_{lex}(e_i, e_j) + \beta . Sim_{sem}(e_i, e_j), \alpha + \beta = 1 \quad (1)$$

Sim_lex employs Levenshtein Distance to match characters, whereas Sim_sem uses cosine similarity to match embeddings from pretrained language models like BERT or Word2Vec. The values of α and β determine how alike the meanings and words are.

2) Normalization of Entities According to Ontology: The study connects each item to standardize diverse words, such as synonyms for the same plant. e_k to its canonical ontology term e^* using a maximum similarity approach, as shown in Eq. (2):

$$e^* = arg \max_{c \in C} (\lambda_1 . Sim_{lex}(e_k, c) + \lambda_2 . Sim_{sem}(e_k, c)) \quad (2)$$

where, C is the set of standard ontology terms. This step makes sure that all the data sources make sense together.

3) Utilizing a Joint Probability Model for Relationship Extraction: The research employed a log-linear conditional model to show the extraction of semantic relations (e.g., Herb–Prescription, Herb–Compound) as demonstrated in Eq. (3), which calculates the probability of a relation r given an entity pair (e_i, e_j):

$$P(r|e_i, e_j) = \frac{exp\left(w_r^T f(e_i, e_j)\right)}{\sum_{r' \in R} exp\left(w_{r'}^T f(e_i, e_j)\right)} \quad (3)$$

The feature vectors f(e_i, e_j) here, semantic embeddings, contextual cues, and grammatical dependencies are examples of textual information. The weight vector W_r is obtained by maximal likelihood estimation (MLE).

4) How to Use Confidence Thresholding to Reduce Noise: Low-confidence triples are removed based on a threshold θ to make sure the data is accurate. This makes the set of relationships easier to read, as shown in Eq. (4):

$$\mathcal{R}_{filtered} = \{(e_i, r, e_j) \in \mathcal{R} | P(r|e_i, e_j) \geq \theta\} \quad (4)$$

This kind of probabilistic filtering increases accuracy by eliminating correlations with little or no evidence. The TCM Knowledge Graph was developed using a multi-stage preparation exercise that draws on concepts in information theory, probabilistic modeling, and ontology alignment in order to ensure it has sufficient structural integrity, meaningful accuracy, and relational connectedness that allows for ease of sharing later.

B. Knowledge Graph Construction

To facilitate the systematic and scalable sharing of Traditional Chinese Medicine (TCM) information, including clinical and cultural information, we constructed a multi-entity, multi-relation knowledge graph (KG). The KG is formally defined as where E is the set of entities, R is the set of relations, and is the set of knowledge triples in the form of (head entity, relation, tail entity). In this situation, entities refer to herbs, prescriptions, illness, chemicals, biological targets, and cultural ideas such as the Five Elements philosophy or Yin–Yang. Relations indicate the semantic and/or therapeutic relationships between those entities, including the Herb–Prescription, Prescription–Disease, and Herb–Compound.

For example, a triplet such as (Ginseng, utilized in Prescription A) exemplifies the function of a plant inside a formulation, whereas (Prescription A, addresses Insomnia) encapsulates the therapeutic application of a prescription. Each entity is represented by ense vector embedding, and each relation is characterized by a transformation function. The semantic plausibility of a knowledge triple is evaluated using a relation score function. In accordance with the translational embedding principle of TransE, the score is determined using Eq. (5):

$$f(h, r, t) = -\|h + r - t\|_2 \quad (5)$$

where, $h, t \in \mathbb{R}^d$ represent the embeddings of the head and tail entities, respectively, and $r \in \mathbb{R}^d$ denotes the embedding of the relation r. Alternatively, to encapsulate more intricate semantic structures, RotatE-based embeddings may be utilized, wherein relations are represented as rotations in complex space, defined in Eq. (6):

$$f(h,r,t) = -\|h \circ r - t\| \tag{6}$$

where, ∘ means the Hadamard product. These formulations make sure that interactions between entities and relations are explicitly described, which makes it possible for computers to reason about them in both clinical and cultural situations.

The knowledge graph (KG) makes the process of diffusion better in a variety of ways. At first, it combines the diverse languages of different data sources to make the message clearer. Secondly, it creates structural connectedness which bridges cultural factors influencing communication contexts with therapeutic knowledge, including herbal remedies, prescriptions, and biological objectives. Ultimately, it extends a computational mechanism for structuring knowledge dissemination routes, meaning that optimal propagation channels must be both culturally relevant and medically sound. The TCM knowledge graph is the primary component for subsequent network modelling and RACO-TCM optimization because it ensures that cultural diffusion is medically appropriate and contextually relevant.

The Traditional Chinese Medicine Integrated Database (TCMID) [26] is used as the central dataset herein since it covers TCM data holistically. To facilitate constructing a highly connected knowledge graph, TCMID provides rich connections between herb prescriptions, chemical compounds, targets, and diseases. It needs a database containing more than 46,000 prescriptions, 8,000 herbs, 25,000 chemicals, and 3,800 biological targets to model culture-treatment interactions. The data entries suit the diffusion network modeling due to the various relation types between them, i.e., herb-prescription, herb-compound, and prescription-disease relations. To cover the linguistic and cultural elements necessary for route planning, we have also integrated extratextual material from cultural communication channels and digital TCM classics. This heterogeneous data ensures an adequate representation of cultural and clinical information. A summary of the dataset is provided in Table I.

C. *Network Modeling*

In the TCM cultural dissemination network, which is shown as a directed graph $G_t = (V, E_t)$, where V is the nodes representing cultural elements such as TCM concepts, media channels, and audience clusters, and E_t is the edges representing possible diffusion routes that change over time. The Dissemination Network Model illustrates how traditional Chinese medicine (TCM) information reaches various audiences through different types of media channels. To ensure a realistic portrayal of cross-cultural communication, as shown in Fig. 2, weights are assigned to each directed edge according to its significance, impact, temporal alignment, and capacity. The RACO-TCM optimization can find efficient, non-redundant distribution routes with the help of this model.

Each edge $e = (i \to j)$ is characterized by several attributes, such as content relevance (r_{ij}), social influence strength (s_{ij}), temporal alignment $(u_{ij}(t))$, and channel capacity (κ_j). The combination of these factors affects the probability of successful propagation across the edge, which is represented by a logistic function that ensures values between 0 and 1, as outlined in Eq. (7):

$$p_{ij}(t) = \sigma\big(\gamma_1 r_{ij} + \gamma_2 s_{ij} + \gamma_3 u_{ij}(t) + \gamma_4 \log(\kappa_j)\big) \tag{7}$$

where, σ(·) stands for the sigmoid activation function, and $\gamma_1, \gamma_2, \gamma_3, \gamma_4$ provide the weightings that show how each part affects the entire. This arrangement combines principles from both social network theory and information diffusion theories and balances the structural and temporal dynamics. There are three ways to evaluate how well a message spreads:

$$P = (v_0 \to v_1 \to \cdots \to v_n)$$

Reachability [R(P)] figures out how many unique people path P is likely to reach by looking at unique audiences at each stage and discounting repetitive exposures, as shown in Eq. (8):

$$\mathcal{R}(P) = \sum_{(i,j)\in P} p_{ij} \cdot \left| A(j) \setminus \bigcup_{(u,v)\in P: v \prec j} A(v) \right| \tag{8}$$

Here, A(j) represents the audience of node j, while $v \prec j$ shows nodes that have been visited before j. Redundancy (D(P)), which punishes people who see the same thing twice to make cultural transmission more efficient, is shown mathematically as Eq. (9):

$$\mathcal{D}(P) = \sum_{(i,j)\in P} \frac{\left| A(j) \cap \bigcup_{(u,v)\in P: v \prec j} A(v) \right|}{|A(j)|} \tag{9}$$

This measure is based on the idea of redundancy, which makes sure that the optimization method focuses on multiple coverage instead of redundancy coverage. The function in Eq. (10) for Time Efficiency [T(P)] finds the overall time delay of the path.

$$\mathcal{T}(P) = \sum_{(i,j)\in P} \tau_{ij}\, , \textit{subject to } t_{k+1} \geq t_k + \tau_{v_k v_{k+1}} \tag{10}$$

with τ_{ij} representing the propagation delay along edge (i,j), and the constraint maintains temporal feasibility. Finally, the overall quality score of a path is demonstrated as a multi-objective optimization function in Eq. (11):

$$J(P) = w_1 . \mathcal{R}(P) - w_2 \mathcal{D}(P) - w_3 . \mathcal{T}(P) \tag{11}$$

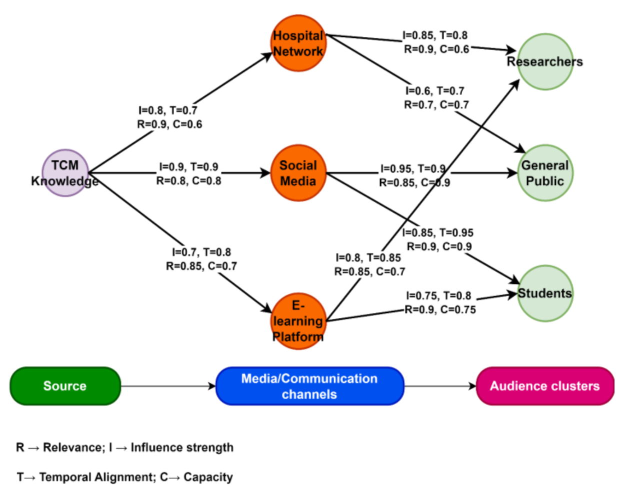

Fig. 2. Temporal dissemination network model.

Here, w_1, w_2 and w_3 , the weights are equalizing importance of the coverage, non-redundancy, and timeliness. This theoretical framework is based on concepts from graph theory, probabilistic diffusion models, and multi-objective optimization. It establishes the next step in developing the RACO-TCM algorithm.

D. Algorithmic Path Optimization (RACO-TCM)

The proposed Reinforced Ant Colony Optimization framework (RACO-TCM) makes dissemination paths more effective by adding dynamic pheromone updates, reinforcement-learning-based reward signals, and redundancy-aware heuristics to standard Ant Colony Optimization. In this system, artificial ants navigate the knowledge network and formulate probable distribution paths through the application of probabilistic decision rules. The likelihood of an ant k transitioning from node i to node j at time t is expressed as Eq. (12):

$$P_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha}.[\eta_{ij}(t)]^{\beta}}{\sum_{l \in \mathcal{N}_i^k}[\tau_{il}(t)]^{\alpha}.[\eta_{il}(t)]^{\beta}} \tag{12}$$

where, $\tau_{ij}(t)$ denotes the pheromone intensity on the edge (i, j), represented as $\eta_{ij}(t)$ signifies its heuristic desirability, α and β represent control factors, and $\mathcal{N}_i^k$ denotes the feasible neighbourhood of ant k. Pheromone trails are continually modified according to Eq. (13) to prevent stagnation and local optima.

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \tag{13}$$

where, ρ represents the evaporation rate, m is the number of ants, and $\Delta\tau_{ij}^{k}(t)$ represents the pheromone deposited by ant k. In contrast to classical ACO, the pheromone deposition is non-uniform and proportionate to a reinforcement incentive that indicates diffusion quality, such that follows the Eq. (14):

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \lambda.R(p^k) & if\ egde\ (i,j) \in p^k, \\ 0, & otherwise \end{cases} \tag{14}$$

where, p^k is the path constructed by ant k, λ is a scaling factor, and $R(p^k)$ is the reward. The reinforcement reward integrates the previously defined multi-objective dissemination metrics and is expressed as in Eq. (15):

$$R(p^k) = \alpha.\frac{\mathcal{R}(p^k)}{max(\mathcal{R})} - \beta.\frac{\mathcal{D}(p^k)}{max(\mathcal{D})} - \gamma.\frac{\mathcal{T}(p^k)}{max(\mathcal{T})} \tag{15}$$

The coefficients $\alpha, \beta,$ and γ govern the balance between optimizing coverage, minimizing redundancy, and decreasing propagation delay. Moreover, the heuristic attractiveness of edges directly integrates redundancy minimization and is stated as in Eq. (16):

$$\eta_{ij}(t) = \frac{R_{ij}.I_{ij}.A_{ij}(t).C_{ij}}{1+\delta.\mathcal{D}_{ij}} \tag{16}$$

where, R_{ij}, I_{ij}, $A_{ij}(t)$, C_{ij} denote the edge properties of relevance, influence strength, temporal alignment, and channel capacity, respectively, while $\mathcal{D}_{ij}$ checks how many people from one node are also in the other, with δ being a punishment coefficient. RACO-TCM combines pheromone enhancement driven by reinforcement with heuristics that are aware of redundancy to find a balance between exploration and exploitation. This solves the problems with classic ACO, such as premature convergence and becoming stuck in local optima. The algorithm gets closer to the best dissemination routes that cover the most ground, cut down on redundancy, and speed up the process. This makes sure that the chosen propagation channels are computationally efficient, culturally relevant, and can be used in other countries.

The below pseudocode shows how the RACO-TCM method works. In this algorithm, numerous ants continually create dissemination channels inside the knowledge graph by combining pheromone intensity and redundancy-aware heuristic values. We use a reinforcement-based reward function to judge each path. This function makes sure that the audience is covered, that there is no redundancy, and that the path is on time. After that, pheromone trails are changed based on the incentive, which guides future searches. The software, via repeated improvements, gets closer to the best ways to spread information that are both effective and culturally appropriate.

Pseudocode: RACO-TCM Path Optimization Algorithm

Algorithm RACO-TCM (Graph G, Parameters $\alpha, \beta, \gamma, \delta, \rho, \lambda, max_{iter}, m$)
Initialize pheromone trails $\tau_{ij}(t) = \tau_0$ for all edges $(i, j) \in G$
For $iteration = 1\ to\ max_{iter}$ do
    For each $ant\ k = 1\ to\ m$ do
        Place ant k at a randomly selected start node
        Construct path p_k using probabilistic rule:
            For each feasible move from node $i\ to\ j$:
                Compute heuristic desirability:
                $\eta_{ij}(t) = \frac{R_{ij}*I_{ij}*A_{ij}(t)*C_{ij}}{1+\delta*D_{ij}}$
                Compute transition probability:
                $P_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha}.[\eta_{ij}(t)]^{\beta}}{\sum_{l \in \mathcal{N}_i^k}[\tau_{il}(t)]^{\alpha}.[\eta_{il}(t)]^{\beta}}$
                Select next node j according to $P_{ij}^{k}(t)$
        End For
        Evaluate path p_k using reward function:
        $R(p^k) = \alpha.\frac{\mathcal{R}(p^k)}{\max(\mathcal{R})} - \beta.\frac{\mathcal{D}(p^k)}{\max(\mathcal{D})} - \gamma.\frac{\mathcal{T}(p^k)}{\max(\mathcal{T})}$
    End For
    Update pheromone trails:
        For each edge $(i, j) \in G$ do
            $\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t)$
            where $\Delta\tau_{ij}^{k}(t) = \lambda.R(p^k)\ if\ (i,j) \in p^k$ else 0
        End For
End For
Return best path p^* with maximum reward $R(p^*)$

E. Parameter Tuning and Reproducibility

Hyperparameters were optimized using a two-stage coarse-to-fine search on temporal divisions of the dissemination network (70/15/15% by time). All edge attributes R_{ij}, I_{ij}, $A_{ij}(t)$, C_{ij}, and overlap $\mathcal{D}_{ij}$ were normalized using min-max scaling to the range [0, 1]. Stage 1 employed a random search across extensive ranges; Stage 2 optimized the top 10 combinations using a neighborhood grid search. The criterion for selection was the average reward $\overline{Q} = \frac{1}{S}\sum_{s=1}^{S} Q(p_s)$; across $S = 5$ seeds; ties were resolved by lower redundancy $\mathcal{D}(p)$.

The reward weights adhered to the simplex constraint $\alpha + \beta + \gamma = 1$, where $\alpha, \beta, \gamma \in [0,1]$. Pheromone was initialized uniformly and thereafter updated by using the following Eq. (17):

$$\left.\begin{array}{c} \tau_{ij}(t) = (1-\rho)\tau_{ij}(t)\sum_k \Delta\tau_{ij}^k(t) \\ \Delta\tau_{ij}^k(t) = \lambda R(p^k)\mathbb{I}\{(i,j) \in p^k\} \end{array}\right\} \tag{17}$$

Subsequent to each update, we constrained $\tau_{ij} \in [\tau_{min}, \tau_{max}]$ for steadiness. The transition algorithm employed exponents on pheromone and heuristic values. To prevent symbol clash with the reward weights, we designate these as α_{aco} and β_{aco}. Early stopping concluded when $|\ \bar{Q}_t - \bar{Q}_{t-10}\ | < 10^{-3}$.

The simplex constraint on i) α, β, γ was kept Q(p) a scale-stable; ii) $\beta_{aco} > \alpha_{aco}$ biases in initial searches favor heuristics, but the impact of pheromones increases as reinforcement builds; iii) $m = \min\{50, \lceil 0.5\ |V| \rceil\}$ moderates exploration expenses in extensive graphs; iv) clipping τ τ inhibits excessive reinforcement and promotes consistent convergence.

The RACO-TCM framework was created to show how Traditional Chinese Medicine (TCM) distribution is based on a relational, holistic, and person-centered concept. It can also improve its technical performance. The framework has algorithms for sharing information that are sensitive to culture and ethics. It does more than only make distribution methods work better for computers. The approach changes how things are distributed based on how involved the audience is, cultural variations in the location, and TCM principles. This means that you need to make sure that the material is provided in a way that makes sense in the context. The model features feedback loops that alter depending on the scenario. In the network, contextual learning helps the framework place culturally significant information like ethical health advice, conventional conceptions, and instructional content ahead of computational goals like coverage, redundancy reduction, and timeliness. This implies that the ideal ways for RACO-TCM to send information are ones that are successful, culturally suitable, ethically sound, and able to satisfy the practical demands of TCM dissemination. Smart cities should make it easier for people to get health care, study online, and enjoy culture.

IV. Results

The experimental setting for evaluating the suggested RACO-TCM framework was put together to make sure it was evaluated in situations that were as close to real life as possible. We used the TensorFlow and PyTorch modules to model optimization and completed all the tests in Python 3.10. Simulations took place on a workstation with an Intel Core i9-13900K CPU, 64 GB of RAM, and an NVIDIA RTX 4090 GPU, which made it possible to handle large datasets and complicated optimization tasks well. Ubuntu 22.04 LTS was the operating system that made it feasible to undertake computational research in a safe environment. To make sure that all of the herbs, prescriptions, compounds, and disorders were in the cultural knowledge graph, the Traditional Chinese Medicine Integrated Database (TCMID) was used. We decided to test RACO-TCM on three base models: TCM-NPG [24], which utilizes neighborhood pruning to promote culture; LMKG-NER [22], a strong knowledge graph that employs named entity recognition to spread TCM; and TCMPS-ARA [25], which uses association rule analysis to enhance placement. Now that we have these standards, we can reliably measure things like distribution efficiency, route redundancy, convergence speed, global search capability, and time.

The efficiency of the RACO-TCM framework in spreading information is a major determinant in how successfully it conveys knowledge about Traditional Chinese Medicine to people from diverse cultures. We figure out how many unique people we contacted compared to how many people we aimed to reach. It is explicitly articulated as $\eta = \frac{\sum_{i=1}^{n}|A_i^{new}|}{|A_{total}|}$, where A_i^{new} shows the new audience at step i, A is the total number of individuals who might view it. A more efficient distribution implies that the framework might help people get information more readily by reducing down on improper communication. Fig. 3 shows that RACO-TCM improves dispersion by 18.6% compared to baseline methods. This demonstrates that it is better at finding the best ways to communicate. This rise shows that the framework not only increases the transmission scale, but it also makes sure that TCM material is always engaging with a wide range of people. This makes the cultural relevance and worldwide influence of TCM material even greater.

Path redundancy looks at how much information an audience gets from different ways of disseminating it. This shows that the way culture is shared isn't working as well as it should. Too much redundancy is doing the same thing over and over again without getting any further with the audience. It is plainly described as $R = \frac{\sum_{i=1}^{n}|A_i \cap A_{prev}|}{\sum_{i=1}^{n}|A_i|}$; this means that A_i is the number of people who have watched the performance up to stage i, and A is the total number of people who have seen it so far. It is easier to share information when there is less redundancy. RACO-TCM reduced route redundancy by 12.3% compared to standard ACO, according to experimental data. As seen in Fig. 4, this might make things more efficient by bringing in new and varied audiences. This cut makes sure that cultural knowledge transfers aren't squandered on items that don't matter. This makes TCM cultural transmission more diverse and accessible to everyone, while being able to flourish over wide and changing networks.

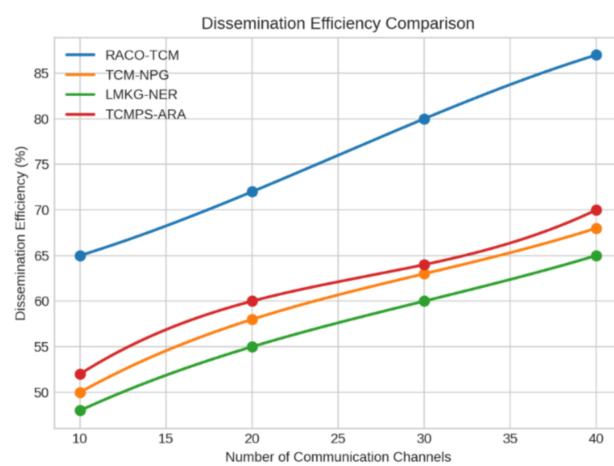

Fig. 3. Comparison of dissemination efficiency among various models.

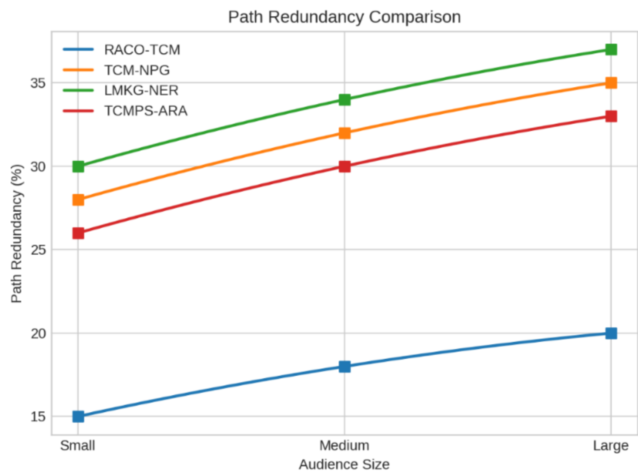

Fig. 4. Comparison of path redundancy for the ACO-TCM vs. Baseline models.

The convergence speed tells us how quickly the RACO-TCM algorithm settles on the best channels for spreading information, which has a direct effect on the cost and flexibility of computing. A faster convergence rate makes it easier to quickly decide on dissemination strategies, which makes it easier to communicate across cultures in fast-changing situations. In technical terms, this is $C_s = \min\{ t \mid \Delta Q(t) < \epsilon \}$, where $\Delta Q(t)$ is the change in the route quality score from one iteration to the next and ϵ is a predefined minimum value. To fulfill this standard, fewer iterations are needed, which implies that convergence comes faster. RACO-TCM converges quicker than ordinary ACO because it incorporates pheromone updates that are driven by reinforcement. This helps it avoid getting stuck and discover quicker pathways than traditional ACO. This characteristic makes the algorithm appropriate for massive, fast distribution initiatives where modifications need to be made quickly. This keeps cultural communication tactics up-to-date and flexible to change with new scenarios, as shown in Fig. 5.

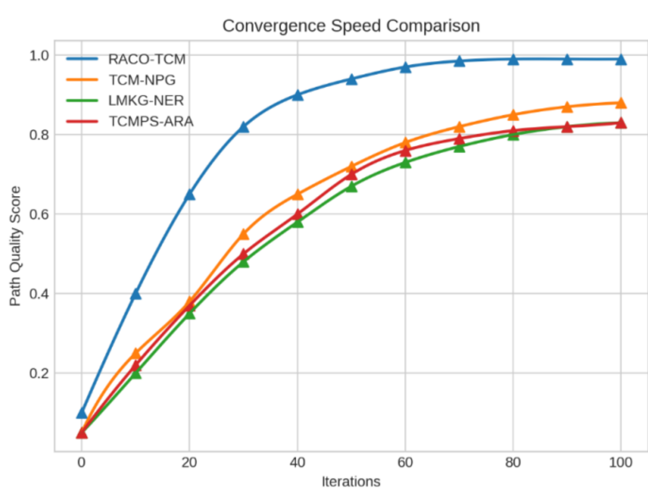

Fig. 5. Analysis of convergence speed based on the RACO-TCM framework.

The global search capacity is an important performance indicator that measures how well the framework can move through a large solution space without becoming stuck in local optima. Rather than hastily opting for suboptimal choices, it guarantees that the algorithm determines the most effective distribution channels worldwide. The metric is expressed as $GSC = \frac{|UniquePaths|}{|TotalExplored|}$; where $|UniquePaths|$ is the number of different high-quality paths discovered and $|TotalExplored|$ is the number of paths that were looked at throughout the optimization. A higher GSC number suggests that the distribution method is more flexible and the exploration options are better. The framework changed pathways in a useful way and reacted to different communication settings by using RACO-TCM's reinforcement-driven exploration, which greatly improved its global search capabilities compared to regular ACO (see Fig. 6). This trait is very important in cultural diffusion networks, as diverse groups of people, media platforms, and contextual factors need to be able to change and adapt. This makes ensuring that cultural outreach isn't constrained by routes that are too narrow or too often.

Time efficiency looks at the whole speed of information transmission to find the average delay across the specified distribution pathways. Good time management makes sure that cultural information gets to the right people quickly, which is very important when people are talking to each other across cultures in real time. It is very evident that $TE = \sum_{(i,j)\in P} \frac{d_{ij}}{|P|}$; where dij is the edge, (i,j) is where the dissemination delay happens, and |P| shows how many pathways were picked in total. When time efficiency values are lower, people may share knowledge faster and don't have to wait as long to join in. RACO-TCM made a lot of progress in reducing propagation delays compared to other approaches. This made sure that cultural messages got to their destinations on time and without any further delays (see Fig. 7). This improvement is especially crucial in the digital era since being on time has a direct impact on how engaged and successful you are. The RACO-TCM framework speeds up the process of sharing information, which helps maintain TCM cultural knowledge relevant to the context and keeps the audience interested.

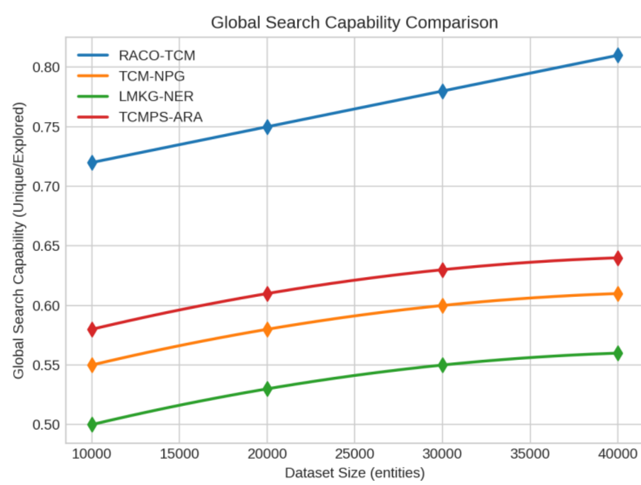

Fig. 6. Global search capability analysis of RACO-TCM compared with the baseline models.

RACO-TCM has been shown to work in a variety of cultural and therapeutic settings. The framework can enable hospitals, community health initiatives, and digital health campaigns to convey correct Traditional Chinese Medicine knowledge as part of their efforts to improve health. Healthcare organizations may make sure that a lot of patients quickly acquire evidence-based TCM information by optimizing how they share it. This will assist people in not getting any wrong idea and promote integrative medicine methods. Second, the algorithm lets digital education platforms disseminate TCM information to students, practitioners, and the general public in a way that is tailored to each group. Integrating with e-learning systems lets you change the way information is shared to get more students involved, cut down on unnecessary repetition in teaching materials, and meet the needs of different cultural or language groups. This makes the knowledge easier to understand and more accessible. Third, RACO-TCM might be integrated into the cultural services of smart cities by becoming part of smart cultural communication systems that employ mobile applications, augmented reality interfaces, and city-wide information networks to disseminate the history of TCM.

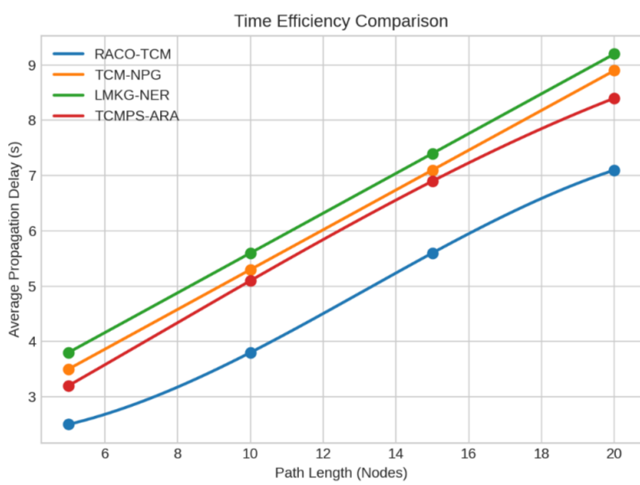

Fig. 7. Comparison of the Time Efficiency metric of RACO-TCM among baseline models experimental discussion.

The algorithm strikes a balance between timeliness, audience variety, and non-redundancy to make sure that past information is preserved and applied in modern smart city ecosystems. This makes people desire to remain being a part of city culture. These applications together show that the suggested method is better than algorithmic efficiency and provides a socially meaningful and scalable framework for spreading Traditional Chinese Medicine (TCM) over the world.

V. Discussion

The research findings demonstrate that RACO-TCM is a useful tool to disseminate knowledge about Traditional Chinese Medicine (TCM) to people from various cultures. The framework not only improves the performance of algorithms, but it also ensures they are usable in the real world by combining heuristics that are aware of redundancy with exploration that is driven by reinforcement.

A. Promoting Health

The technology makes it possible to quickly and accurately communicate TCM information through hospitals, community events, and online marketing. To improve integrative healthcare practices, the best way to convey information to patients is to make sure that evidence-based TCM knowledge gets to as many people as possible.

Digital education systems like RACA-TCM let you communicate TCM material with students, practitioners, and the general public in a way that works for them. By cutting down on repetition and adapting routes to meet the audience and cultural context, the framework makes learning simpler, more fun, and easier to grasp.

B. Smart Cities' Cultural Services

The framework protects and expands TCM culture in cities by using augmented reality interfaces, smartphone applications, and smart city platforms. RACO-TCM finds a balance between being timely, having a wide range of audiences, and not being redundant. This encourages people to stay involved with culture and employ old knowledge in their daily lives.

C. Overall Impact

RACO-TCM has a socially relevant, scalable, and culturally integrated way of getting Traditional Chinese Medicine (TCM) to people that goes beyond just numbers. It uses mathematical optimization and takes into account the audience and the setting in which the information will be seen to make sure that cultural material is not only distributed quickly but also engaging and useful to the people who will see it.

D. Limitations

The Traditional Chinese Medicine Integrated Database (TCMID) is the major source of information that is being utilized in this specific inquiry. It is feasible, however, that the results will be different when applied to other datasets or when utilized in various cultural settings. This is something that should be taken into consideration. As a result of the fact that the framework needs a substantial amount of computing power in order to conduct out simulations on a large scale, it is possible that it is not straightforward for everyone to use. Additionally, it is likely that some of the assumptions that are utilized in the process of modelling networks and developing knowledge graphs, such as edge weights and audience behavior, may not accurately portray the method in which things are complicated in the actual world. This is something that is a possibility. Furthermore, in spite of the fact that it has been optimized for TCM distribution, it may still be necessary to perform extra tuning and validation in order to adapt to a variety of domains or cultural knowledge networks.

VI. Conclusion

The RACO-TCM framework provides a reinforcement-enhanced Ant Colony Optimization technique for cultural dissemination, effectively resolving significant issues of duplication, inefficiency, and restricted flexibility inherent in conventional heuristic models. The method works really well since it involves making a knowledge graph, looking at a temporal network, and improving a number of goals. This makes distribution more efficient, cuts down on path redundancy, and speeds up experimental assessments. These results indicate that it can be both analytically accurate and culturally relevant. It can be used in many ways to improve healthcare, digital learning, and cultural services in smart cities. There are still certain constraints, though. The system is built on set reward weights. Changing the parameters makes the system more stable, but it is still not clear how to change these weights in networks that are continually changing in the real world. The current evaluation primarily utilized simulated dissemination networks; more validation using extensive, real-world TCM communication systems is necessary to confirm robustness. It could be required to employ parallel or distributed computing technologies to make big graphs work with many computers at once. Future research will focus on developing adaptive reward systems that respond to contextual variations, improving the model to incorporate multimodal dissemination platforms, such as video or augmented reality, and integrating federated optimization to facilitate privacy-preserving and cross-regional cultural knowledge exchange. The goal of these recommendations is to make RACO-TCM a long-lasting framework for smart cultural communication in a world that is always changing.

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