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IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 14 March 2026, accepted 23 March 2026, date of publication 26 March 2026, date of current version 9 April 2026.

Digital Object Identifier 10.1109/ACCESS.2026.3678205

RESEARCH ARTICLE

Efficient Algorithm to Find Influential Nodes Using Community-Based Hybrid Centrality in Complex Networks

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This work was supported by the SRM University-AP towards the Article Processing Charges (APC).

ABSTRACT Finding influential nodes is a crucial task for understanding and optimizing information spreading in complex networks such as social, biological, transportation, and technological networks, where group-based interactions are common and efficiently represented by using hypergraphs. Traditional centrality measures fail to capture the nuanced relationships in inherent hypergraph structures. To overcome these limitations, we propose a novel centrality measure Isolating Relative Average Shortest Path (IRASP), by combining both isolating centrality and relative average shortest path. It considers both neighborhood structure, path connectivity, and the relative change of shortest path in the hypergraph after removing the node. In addition to our study, we integrated hypergraph community detection to refine and ensure the structural modularity to select diverse influential nodes. IRASP achieves higher efficiency than existing centrality measures by leveraging local structure and relative path changes. When combined with community detection, it significantly reduces computation time, making it well-suited for large-scale hypergraphs. We evaluated our method on six real-world hypergraph datasets, by employing the Kendall Tau correlation and diffusion model on community structures. Integrating community detection significantly reduces the computation time, making IRASP particularly effective for large-scale hypergraphs and improving influence detection up to 0.05%.

INDEX TERMS Hypergraphs, centrality measures, isolating relative average shortest path, isolating centrality, influential nodes.

I. INTRODUCTION

Nowadays, various higher-order networks such as biological networks, social networks, and collaboration networks are involved in group interactions. Traditionally, these networks are dyadic and represented as graphs, where nodes are users and edges denote pairwise interactions [1], [2]. Many real-world interactions involve higher-order systems, which can be represented as hypergraphs. Higher-order interactions are represented by hypergraphs, where the hyperedges contain an arbitrary number of nodes and capture multi-way interactions beyond pairwise relationships [3], [4].

The associate editor coordinating the review of this manuscript and approving it for publication was Yang Tang.

Hypergraphs are a generalized form of graph, allowing hyperedges to connect more than two nodes [5]. A key challenge in complex networks is detecting the influential nodes that can optimize diffusion and improve robustness [6]. Centrality measure is a quantitative tool that will assess the efficiency of node based on its structural position in the entire network [7]. Hypergraph centrality measures are extended from graphs, such as degree centrality (DC), betweenness centrality (BC), closeness centrality (CC), gravity, and harmonic centrality (HC) [8]. These are some basic centrality measures that mainly focus on the immediate neighbors and shortest paths. Some recent centrality measures, such as isolating centrality (ISC) [9] and local relative average shortest path (LRASP) [10] mainly focus on the relative change in a hypergraph when a particular node is removed. The existing centrality measures concentrates on local and global structure of a network. To overcome the limitations of earlier methods, we introduce an integrated approach, Isolating Relative Average Shortest Path (IRASP), which merges neighborhood-level and network-wide metrics in order to improve the detection of influential nodes across a network. IRASP is incorporated with two centrality measures, ISC and RASP, which focuses on relative change in the network after node removal. Applying these measures to various real-world hypergraph datasets like social, communication, and biological networks.

Our primary research focuses on detecting influential nodes by incorporating community detection into our work to enhance information flow [11], [12], [13], [14]. Researchers often convert hypergraphs into 2-section graphs, where hyperedges are replaced with cliques, and then apply algorithms such as Louvain [15] and Leiden [16]. Another way to cluster nodes is to use their distances from the derivative graph, as Contreras-Aso et al. [17] suggest. Afterwards, choose the segments which provide the best modularity in a 2-section graph. However, this approach fails to capture important structural details about hyperedges due to transforming a hypergraph into a 2-section graph often leads to information loss. Chodrow et al. [18] introduced a stochastic block model for hypergraphs, which is guided by a Louvain-type clustering algorithm. This approach enhances modularity by connecting edges that contain nodes from the same community. These approaches for finding communities, apply the modularity function [19] to produce standard partitions in the network. Louvain and Leiden community detection algorithms are widely used for graph structures. For hypergraphs, Kumar et al. [20], [21] introduced the hybrid clustering method named Kumar's, which is integrated with both the Louvain and 2-section graphs to enhance the detection of community partitions. While Kumar's method still reduces the limitation of graphs, by iteratively adjusting the weights in hypergraph. Modularity serves as a metric for assessing community detection quality by quantifying the extent to which nodes in a community are connected via hyperedges to nodes outside their community. In our work, we used Kumar's community detection method to improve partitions in hypergraphs without losing the information. In section V, we briefly discuss the Kumar's community detection method.

By considering these methods in our study, we defined an algorithm for seed node selection in hypergraphs that integrates both community structure and centrality measures. Kumar's community detection method enhances the node's effectiveness within the community and distributes seed nodes across well-defined groups in the hypergraph. For each community, the centrality measures are evaluated to identify influential nodes. This hybrid centrality measure approach captures the local information as well as the flow of connectivity and the capacity of local nodes in a hypergraph whose connectivity is low. To check the efficiency of our proposed method on the community structure of hypergraphs, Kendall Tau method assess correlation between the ranks, and a diffusion model checks how information propagate between both existing and recent measures. The proposed method on community structure performs superior in terms of information spread and computational time.

Specifically, the primary contributions of this paper are highlighted as follows.

- We propose a community-based framework for capturing influential nodes and verified the performance by using centrality measures within the detected communities across the entire network. Our measure ensures a balanced representation of influence on different networks.
- The IRASP, a novel hybrid centrality measure that incorporates local structure influence via Isolating Centrality (ISC) and global influence through Relative Average Shortest Path (RASP). This allows the measure to capture both immediate neighborhood and network-wide reach.
- Unlike the other centrality measures rely on static structural features, our centrality measure evaluates node influence based on the structural disruption occurred by node isolation. This provides a superior assessment of node's actual importance, while spreading the information to the overall network.
- The methodology is focused on the hybrid centrality measure IRASP and community detection. Evaluated all centrality measures on communities and extracted seed nodes from each community. By using these seed nodes we observed the influence of information spreading across the network.

Our research work is arranged in the following manner: Section II, outlines the appropriate applications of our research work. Section III gives brief introduction on background work of recent and basic community detection methods. In section IV, a brief review of the existing centrality measures, based on these limitations, section V introduces a proposed centrality measure. Section VI gives out brief description of real-world datasets and evaluation metrics. In section VII, the experimental results are discussed. Finally section VIII delivers the conclusion and future work.

II. APPLICATIONS

In e-commerce sites, items are often buy or view in groups, reflects their higher-order-interactions among the items. Designing these interactions as hypergraphs permits for capturing the subtle preferences of consumers. By employing centrality measures specific groups of products, businesses can detect important products that boost sales in specific segments, dominant to more competent recommendation systems and marketing strategies [22]. In collaboration network the multiple authors involve in single publication, represents higher-order interactions that go beyond simple pairwise relationships. Graph based models, represent these collaboration as dyadic relationships between pair of authors, fail to capture the complexity of group collaborations. To address this, the hypergraphs provide a expressive framework by allowing hyperedges to connect multiple author collaborations [23]. Identifying key authors or influential research groups, by applying centrality measures for communities which are segmented from hypergraphs. This enables collaborating bridging, facilitate knowledge diffusion and covers the impact research groups within specific scientific domains. In transportation networks, certain merging spots may results a substantial impact on operating the whole network [24]. Finding key propagators is very important for preventing the dissemination of infectious diseases in the field of disease spreading [25]. In biomedical networks, interactions involve in multiple entities, such as protein interactions or metabolic pathways represents the multi way relationships. These interactions are represented as hypergraphs, by employing centrality measures within the communities can detect critical genes or proteins that play a key roles in particular biological structures, and in disease mechanisms [26]. This process improves our knowledge on complex biological networks and can accelerate the drug target discovery.

III. LITERATURE REVIEW

In recent years the researchers have been interested to apply hypergraphs in complex networks to enhance the connectivity of multiple nodes and to capture group dynamics. The foundational work was initiated by Berge in 1973 [5], to analyze the higher-order networks, it may include irrelevant data and noisy interactions, which can block out the dominant structural or functional patterns. To overcome this challenge, we adopt community detection, which permits us to focus on more reliable and relevant substructures within the hypergraph and inflate both interpretability and computational efficiency.

Ruggeri et al. [27] introduced a probabilistic generative model (Hy-MMSBM) for community detection in hypergraphs, which permits mixed memberships and captures both assortative (nodes within a community interact more) and disassortative (nodes from distinct communities interact more) structures. This is a significant advantage for this generative model, as the previous models often restricted up to assortative interactions only. The Hy-MMSBM method is more suitable for large-scale hypergraphs, containing interactions among thousands of nodes. Kaminski et al. [28] introduced the concept of modularity as a quality function for identifying the communities in a graph extended to hypergraphs. This modularity function is the extension of configuration model and specific hypergraph properties. It follows the classic louvain method employed to hypergraphs, producing ambiguous community partitions. To overcome this limitation, the h-louvain has been proposed. The main advantage is that it can operate on large hyperedges efficiently compared with previous community detection methods. h-Louvain is highlighted by resolving the limitation of direct hypergraph modularity optimization by dynamically blending with two-section graph modularity to identify meaningful communities in the hypergraph. Kumar et al. [29] introduced isochronous temporal metric to integrate neighborhood with time-based methods to identify effective tasks such as neighbors classification and clustering. This approach highlights the distance based neighbourhood selection. In this the nearest neighbor technique is used to compute classification accuracy and clustering is evaluated by using adjusted random index.

Kovacs et al. [30] broaden the k-clique percolation to find communities in general hypergraphs and proposed two distinct perspectives that prioritize large hyperedges and focus on smaller hyperedges, replicating distinct community formation rules. This method mainly focuses on synthetic hypergraph datasets, it provides flexibility to find community structures based on hyperedge sizes. Recently, Ni et al. [31] introduced the Multi-Hypergraph-Stochastic Block Model (MHSBM) highlights integrating information from multiple hypergraphs to handle heterogeneity and inter-hypergraph interactions. It mainly highlights the concept of hyperedge internal degree to compute node contributions. Kumar et al. [21] proposed a hybrid clustering algorithm for hypergraphs that operates on two-section graphs and subsequently utilizes the Louvain algorithm. In this two-section graph, weights are reweighted based on the shared vertices within each hyperedge. This algorithm enhances community partitions by employing the modularity function in hypergraphs.

Once the hypergraph is partitioned into distinct communities, a core motivation of our work is to investigate the significance of individual nodes and their capacity to disseminate information throughout the network. To achieve this, a key objective is the identification of influential nodes within these complex network structures. Centrality measures are introduced to quantify the importance of a node in social network analysis, and developed some basic centralities in graphs. The basic centrality measures are degree, betweenness, closeness, and harmonic metrics to quantify the node importance based on their position in the network. Some centrality measures are extended to hypergraphs, such as hyperdegree, degree, closeness, betweenness, harmonic, and gravity, etc and these measures are discussed in subsequent sections.

IV. REVIEW OF HYPERGRAPH CENTRALITY MEASURES

A hypergraph $H = (V, E)$ is a generalized form of a graph, where V is a set of nodes and E is a set of hyperedges. Each hyperedge contains more than two nodes and also captures higher-order relationships. To determine the influential nodes in a hypergraph, various centrality measures are existed. Some are degree centrality (DC), betweenness centrality (BC), closeness centrality (CC), isolating centrality (ISC), and harmonic centrality (HC) etc.

TABLE 1. Categorizing of local, global, and hybrid centrality measures with rationale.

Centrality Measures	Category	Rationale
Degree Centrality (DC)	Local	Depends on intermediate node connectivity and incident hyperedges.
Neighbor-Degree Centrality (NDC)	Local	Quantifies the node influence based on the connectivity of immediate neighbors.
Line -Expansion Degree Centrality (LED)	Local	Captures the local connectivity of hyperedges by their shared node interactions.
Betweenness Centrality (BC)	Global	Quantifies the shortest paths between all node pairs.
Closeness Centrality (CC)	Global	Depends on average shortest path distance to all the nodes.
Harmonic Centrality (HC)	Global	Based on the inverse distances to all the nodes in the hypergraph.
Isolating Centrality (ISC)	Local	Quantifies local structural connection loss occurred by node removal.
Relative Average Shortest Path (RASP)	Global	Compute the global average shortest path variation when the node is removed from hypergraph.
Isolating Relative Average Shortest Path (IRASP)	Hybrid	Combines both local (ISC) and global (RASP) centrality measures.

A. DEGREE CENTRALITY (DC)

Degree centrality measures a node's significance by capturing the number of hyperedges containing that node [5]. It identifies the nodes that are highly connected and locally influential in terms of direct connections. The mathematical representation of degree centrality of a node is computed by Eq. 1:

$$DC(v_i) = \frac{\sum_{k=1}^{m} a_{ik}}{n-1} \tag{1}$$

where, n stands for node count, m is count of hyperedges in a hypergraph and i, k are rows and columns of adjacency matrix.

B. CLOSENESS CENTRALITY (CC)

It demonstrates the node significance based on, how closely a particular node interacts with the other nodes. Works based on the shortest paths between two nodes [32]. CC is mathematically computed by using Eq. 2

$$CC(v_i) = \frac{n-1}{\sum_{u_i \neq v_i \in V} d(v_i, u_i)} \tag{2}$$

where the shortest path length between pair of (v_i, u_i) is defined as $d(v_i, u_i)$. Nodes that posses high CC value can swiftly connect to all other nodes and are globally central in the hypergraph.

C. BETWEENNESS CENTRALITY (BC)

Determine the significance of a node by assessing the amount of shortest paths in which it acts as an intermediary [33], [34]. A high BC value of a node enables strong connectivity of the network. BC is computed by Eq. 3

$$BC(v_i) = \sum_{s \neq v_i \neq t} \frac{\sigma_{st}(v_i)}{\sigma_{st}} \tag{3}$$

where the shortest route between s and t is given as σ_{st}, $\sigma_{st}(v_i)$ represents where a node v_i that act as intermediary in shortest path between s and t.

D. HARMONIC CENTRALITY (HC)

Harmonic centrality (HC) measures the significance of a node by aggregating the shortest path lengths from one node to remaining nodes of the network [35] is computed by using Eq. 4

$$HC(v_i) = \sum_{u_i \neq v_i} \frac{1}{d(v_i, u_i)} \tag{4}$$

where $d(v_i, u_i)$ is shortest route between the node v_i and to other node u_i. HC is a variant of closeness centrality, which can capture the reachability of a node in disconnected networks.

E. NEIGHBOR-DEGREE CENTRALITY (NDC)

Neighbor-degree centrality (NDC) is a local measure that quantifies the influence of node based on their connectivity of its immediate neighbors [36]. Neighbor-degree centrality checks the importance of neighboring nodes. Let $H = (V, E)$, V be the number of nodes and E is number of hyperedges. It is mathematically computed by using Eq. 5.

$$C_{NDC}(v_i) = \frac{|N(v_i)|}{|n| - 1} \tag{5}$$

For a node $v \in V$ the neighbor set of v is defined as

$$N(v_i) = \{ v_i \neq u_i \in V \mid \exists e \in E \text{ such that } \{u_i, v_i\} \subseteq e \}.$$

where $N(v)$ contains all the nodes that are occurred with v at least in one hyperedge.

F. LINE-EXPANSION DEGREE CENTRALITY (LED)

In line expansion each hyperedge becomes a node and adjacency is defined between hyperedges [36]. Line-expansion degree centrality measure is basically for hyperedges. Let $H = (V, E)$, V is set of nodes and E is set of hyperedges.

The line expansion of H is $L(H) = (E, E_L)$, where each node in $L(H)$ corresponds to a hyperedges. The two nodes e, e' are adjacent in $L(H)$ if and only if the hyperedges are adjacent in H. Steps to calculate LED for each node:

(1) For any two hyperedges $e_i, e_j \in E$, define the adjacency value.

$$A(e_i, e_j) = \begin{cases} 1, & \text{if } e_i \cap e_j \neq \emptyset \\ 0, & \text{otherwise} \end{cases}$$

(2) Line expansion degree of hyperedge e_i is defined as:

$$\mathrm{LED}(e_i) = \sum_{\substack{e_j \in E \\ j \neq i}} A(e_i, e_j)$$

(3) For a node $v \in V$, define the incident hyperedge set.

$$E(v) = \{e \in E | v \in e\}$$

(4) The normalized LED for node-level is calculated as:

$$C_{LED}(v_i) = \frac{1}{|E(v)|} \sum_{e \in E(v)} LED(e) \tag{6}$$

The LED(v) captures the importance of a node based on the interactions of its incident hyperedges and exhibits a node-level centrality captured from hyperedge based line expansion.

G. ISOLATING CENTRALITY (ISC)

Isolating centrality evaluates the node influence through its degree and minimal degrees of it neighboring nodes. Isolating coefficient is defined as the number of neighboring nodes with the smallest degree connected to a given node [9], [37]. The isolating coefficient is used to assess the node's significance by disconnecting the network. The ISC is mathematically represented as Eq. 7.

$$ISC(v_i) = |N(v_i) \cap Deg_\delta| \times \frac{deg(v_i)}{n} \tag{7}$$

$N(v_i)$ neighbors of node v_i, the set of vertices which has a minimum degree is given as Deg_δ, and while the degree of node v_i is $deg(v_i)$. Degree centrality is a critical component of isolating centrality, however there is an significant distinction between them. According to isolating centrality, if neighbor nodes have a minimum degree, then it becomes a highly influential node rather than a node with a high degree. This states that removing such nodes can separate the network into fragments and disconnect the hypergraph.

H. RELATIVE AVERAGE SHORTEST PATH (RASP)

Lv et al. [38] introduced the concept of relative average shortest path in graphs, where it emphasis on structural properties of the path. In our work, we extend this concept into hypergraphs where the RASP serves as a global centrality measure, and it captures the broader structure of the hypergraph. It captures the relative change in shortest paths when the node is removed from entire network. RASP evaluate the shortest routes among all pair of nodes when the node is removed from a network [10]. The RASP is mathematically computed by Eq. 8

$$RASP(v_i) = \frac{|ASP[H'_{v_i}] - ASP[H]|}{ASP[H]} \tag{8}$$

where $ASP[H'_{v_i}]$ represents the average shortest path of a hypergraph after removing a node and its corresponding hyperedges, and $ASP[H]$ is the average shortest path of a hypergraph.

I. SHORTEST PATHS (SP)

A hypergraph $H = (V, E)$, is a collection of nodes and hyperedges, where each hyperedge represents an interaction among an arbitrary number of nodes. In our work the hypergraph structure is considered as edge-list, rather than transforming to clique-expansion or to simple graph representation. The shortest path (SP) between two nodes is defined as the minimum number of hyperedges are involved to connect them through a hyper-path. A hyper-path between two nodes in a hypergraph is defined as an ordered sequence of nodes and hyperedges, where each consecutive step occurs between nodes belonging to the same hyperedge. The length of a hyper-path between any two nodes v_i and v_j, denoted by ℓ_{ij}, is defined as the number of hyperedges traversed. Accordingly, the shortest path distance between v_i and v_j is computed as Eq. 9.

$$d(v_i, v_j) = \min \left\{ \ell_{ij} \,\middle|\, \text{a hyper-path exists between } v_i \text{ and } v_j \right\}. \tag{9}$$

Consider nodes V and hyperedges E

$$V = \{1, 2, 3, 4, 5\}$$
$$E = \{e_1 = \{1, 2, 3\},\ e_2 = \{3, 4\},\ e_3 = \{4, 5\}\}.$$

Compute the SP for node 1 and node 3,

$$d(1, 3) = 1 \quad \text{(nodes 1 and 3 share the same hyperedge)}$$

Likewise, the SP between the node 1 and node 5 is 3,

$$d(1, 5) = 3 \quad \text{(traverse three hyperedges } e_1, e_2, e_3\text{)}.$$

The shortest path distance represents the minimum number of group relationships required to enable information spreading between the nodes.

J. AVERAGE SHORTEST PATH (ASP)

It is defined as the average number of walks required to travel from one node to other nodes in a network, considering the minimum-length walk between each pair of nodes [38], [39]. In our work, the network is depicted as a hypergraph, and the ASP is computed using Eq. 10

$$ASP(H) = \frac{\sum_{u_i \neq v_i \in V} d(v_i, u_i)}{n(n-1)}. \tag{10}$$

Here, $d(v_i, u_i)$ denotes the shortest-path distance between a pair of nodes, and n represents the total number of nodes in the hypergraph. ASP evaluates the overall reachability of nodes:

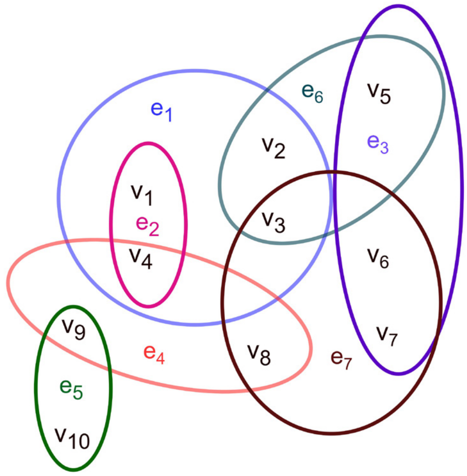

FIGURE 1. Hypergraph with 10 nodes and 7 hyperedges.

if a node pair is reachable, the corresponding shortest-path length is considered; otherwise, the network diameter is used as the distance.

Existing centrality measures such as degree, closeness, betweenness and harmonic mainly focus on the structural information, like capturing the neighbor nodes and shortest distances travel from one node to other node. Existing measures focus on local structure it is computationally less, but ignores the impact of neighbor nodes leads to less connectivity and loose the influential global nodes in the hypergraph. The degree centrality mainly focus on the local information of a node and ignores the global structure. The global centralities like closeness centrality depends on the shortest paths and traverse all the nodes and betweenness centrality focus on the nodes that act as bridge between two nodes when we are computing the shortest paths. These methods are unstable when any change occurred in the network, and the nodes influence can be overestimated in these cases. Neighbor-degree centrality focus on immediate neighbors and neglects high-order information. It does not check the influence of the connected neighbors. Line-expansion degree centrality is sensitivity to hyperedge size, where large hyperedges intersect with more number of hyperedges, leads to inflated ratings that affect the structural influence. ISC focuses on local neighborhood and computes node influence based on their isolation effect and it does not capture the node removal on global connectivity. RASP depends on the paths, where the node is removed it capture the relative change in the network and it is insensitive to local neighborhood structure. Considering this research gap, we focus on both local and global centrality measures and proposed a hybrid centrality. The rationale and categories of existing centrality measures are shown in Table. 1. Additionally to reduce the computation time, we integrated community structure to our research work. In the following section, we given a detailed description of hybrid centrality, community detection method and workflow of our proposed work.

V. PROPOSED CENTRALITY

The key motivation for proposing IRASP (Isolating Relative Average Shortest Path) is to capture structural properties of hypergraphs by combining two complementary centrality measures, Isolating Centrality (ISC) and Relative Average Shortest Path (RASP). Specifically, ISC captures the isolating influence of a node within its local hypergraph structure by showing how the removal of a node affects the connectivity and structural dependency of neighboring nodes. In contrast, RASP computes the relative change in the average shortest path and highlights a node's contribution to maintaining efficient information propagation within the local neighborhood. Since ISC depends on node isolation and RASP relies on path-based influence, each measure individually may not capture node influence across multiple structural dimensions in a hypergraph. Therefore, the proposed framework integrates these measures using a tunable parameter α, enabling a balanced evaluation of both ISC and RASP.

A. ISOLATING RELATIVE AVERAGE SHORTEST PATH

In this section, we introduced a hybrid centrality model, Isolating Relative Average Shortest Path (IRASP), which incorporates both the isolating centrality (ISC) and relative average shortest path (RASP) centrality measures to assess the node influence on both local and global scales. RASP centrality quantify the impact of a node on a global structure of a hypergraph by examining the change in average shortest path length among pairs of nodes when a specific node is removed. Isolating centrality concentrates on the idea of a node's isolation by evaluating the level to which a node is isolated from the other nodes in the hypergraph. By combining these local and global metrics, we propose the IRASP of a node is computed by Eq. 11

$$IRASP(v_i) = \alpha * ISC(v_i) + (1 - \alpha) * RASP(v_i) \tag{11}$$

where, the tunable parameter α controls the balance between local and global influences with in the proposed measure and it ranges from 0 to 1 [7]. We adjust the α value to tune the measure and prioritize either local influence or global influence. The $ISC(v_i)$ measures the isolating centrality for a particular node and $RASP(v_i)$ is the relative average shortest path of v.

To enable a balanced combination between isolating centrality and relative average shortest path, we normalize them by using min- max normalization across all the nodes in the network (hypergraph). The normalized values are defined as:

$$\widetilde{ISC}(v_i) = \frac{ISC(v_i) - \min_{v \in V} ISC(v)}{\max_{v \in V} ISC(v) - \min_{v \in V} ISC(v)},$$
$$\widetilde{RASP}(v_i) = \frac{RASP(v_i) - \min_{v \in V} RASP(v)}{\max_{v \in V} RASP(v) - \min_{v \in V} RASP(v)}.$$

These normalized components rely between the interval [0,1]. The proposed IRASP centrality is computed as convex

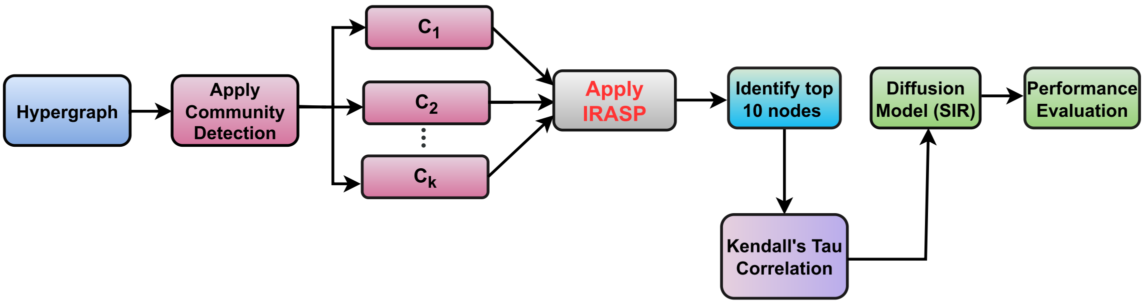

FIGURE 2. **Procedure for evaluating influential nodes in hypergraph using community detection.**

combination with these normalized components:

$$IRASP(v_i) = \alpha \cdot \widetilde{ISC}(v_i) + (1-\alpha) \cdot \widetilde{RASP}(v_i), \quad \alpha \in [0, 1]. \tag{12}$$

The parameter α controls the relative importance of local and global influence. When α is 1, IRASP highlights local isolation captured by ISC. Conversely, α is 0, IRASP prioritizes global connectivity captured by RASP. By normalizing the components, both the local and global influence contributed proportionately to IRASP, and enables a balanced integration.

Traditional centrality measures such as DC, CC, BC, and HC either focus on immediate neighborhood structure or shortest-path routing frequency, often neglecting the structural consequences of node removal. Isolating centrality improves upon degree centrality by considering neighbor vulnerability, yet still operates locally. IRASP differs fundamentally by explicitly modeling network response under node deletion, thereby quantifying influence through structural degradation. This makes IRASP particularly suitable for identifying critical articulation-like nodes in hypergraphs where higher-order interactions dominate.

Proposition 1: Let v_b be a bridging node connecting two or more hypergraph communities, and let v_l be a locally isolated node whose neighbors possess minimum degree within a single community. The proposed IRASP centrality assigns a higher score to v_b than to v_l if and only if

$$(1-\alpha)\,[RASP(v_b) - RASP(v_l)] > \alpha\,[ISC(v_l) - ISC(v_b)], \tag{13}$$

where $\alpha \in [0, 1]$.

Proof: The IRASP centrality of a node v is defined as

$$IRASP(v) = \alpha \cdot ISC(v) + (1-\alpha) \cdot RASP(v), \quad \alpha \in [0, 1]. \tag{14}$$

We compare the IRASP scores of nodes v_b and v_l:

$$IRASP(v_b) > IRASP(v_l). \tag{15}$$

Substituting the definition of IRASP yields

$$\alpha\, ISC(v_b) + (1-\alpha)\, RASP(v_b) > \alpha\, ISC(v_l) + (1-\alpha)\, RASP(v_l). \tag{16}$$

Rearranging terms gives

$$(1-\alpha)\,[RASP(v_b) - RASP(v_l)] > \alpha\,[ISC(v_l) - ISC(v_b)]. \tag{17}$$

From a structural perspective, node v_b participates in inter-community hyperpaths. Its removal therefore induces a substantial increase in the average shortest path of the hypergraph, implying

$$RASP(v_b) \gg RASP(v_l). \tag{18}$$

In contrast, node v_l is primarily connected to low-degree neighbors within a localized region, resulting in a stronger isolation effect and hence

$$ISC(v_l) > ISC(v_b). \tag{19}$$

Consequently, when the global structural disruption caused by removing v_b outweighs the local isolation strength of v_l under the weighting parameter α, the IRASP measure prioritizes the bridging node. □

Correctness: The result logically follows from the definition of the IRASP measure as a convex combination of the ISC and RASP measures. The algebraic manipulation from the inequality $IRASP(v_b) > IRASP(v_l)$ to the derived result is legitimate. The logical justifications for the conditions that a bridging node v_b will induce a greater average shortest path disruption when removed ($RASP(v_b) \gg RASP(v_l)$), and a locally isolated node v_l will induce a greater isolation centrality measure ($ISC(v_l) > ISC(v_b)$), are reasonable assumptions based on the nature of the hypergraph. However, these are assumptions rather than demonstrated facts. The conditions collectively ensure that for a small value of α that emphasizes global structure over local isolation, the inequality

$$(1-\alpha)[RASP(v) - RASP(v_l)] > \alpha[ISC(v_l) - ISC(v)]$$

is satisfied for the ranking of v_b above v_l to hold. This demonstrates the validity of the IRASP measure in correctly trading off inter-community bridging importance against intra-community isolation strength. The above proposition establishes IRASP as a context-sensitive centrality mechanism whose behavior adapts according to the weighting parameter α. When α takes smaller values, the global

Algorithm 1 Community-Based Seed Node Selection Using Centrality in Hypergraphs

Require: Hypergraph $HG = (V, E)$, Number of seeds k
Ensure: Selected seed nodes S
Step 1: Community Detection
Partition the hypergraph into communities: $\mathcal{C} \leftarrow \text{CD}(HG)$ /* we used Kumar's community detection method */
Step 2: Initial Seed Selection
Initialize seed set $S \leftarrow \emptyset$
for each community $C_i \in \mathcal{C}$ **do**
  Extract sub-hypergraph HG_i induced by C_i
  Compute centrality score $C_i(v)$ for nodes v in HG_i based on IRASP in Eq. 11
  Select top-ranked node $v^* \leftarrow \arg\max_{v \in C_i} C_i(v)$
  $S \leftarrow S \cup \{v^*\}$
end for
Step 3: Allocate Remaining Seeds Based on Community Size
$r \leftarrow k - |S|$ {Remaining seeds to allocate}
for each $C_i \in \mathcal{C}'$ **do**
  if $r \leq 0$ **then**
    break
  end if
  Identify additional top-ranked nodes in C_i not already in S based on size of C_i
  Select up to r and add them to S
  Update $r \leftarrow k - |S|$
end for
Step 4: Return Final Seed Set
return S /* S has top k seed nodes */

component $RASP(\cdot)$ dominates, causing IRASP to prioritize bridging nodes whose removal leads to substantial inflation in average shortest path lengths and disruption of inter-community information flow. As α increases, the contribution of the local isolation component $ISC(\cdot)$ becomes more pronounced, resulting in a preference for locally isolated nodes whose removal fragments dense neighborhood structures. For intermediate values of α, IRASP achieves a balanced evaluation by jointly capturing global structural degradation and local isolation effects, thereby enabling controlled trade-offs between network resilience assessment and localized vulnerability identification. This adaptive property theoretically validates IRASP as a tunable and structurally grounded centrality measure for influence analysis in hypergraphs with heterogeneous connectivity and higher-order interactions.

B. COMMUNITY DETECTION

In our work, we focus on the community detection on hypergraphs to identify densely connected nodes in the network. The community detection function act as a pipeline to enhance the computational efficiency and allows to select the seed nodes accurately. After partitioning the hypergraph, using community detection method, the proposed metric is evaluated for each community. It reduces the problem size, while preserving higher-order information. Adding community detection into our work does not bias the influence selection toward modular nodes, as the IRASP measure integrated both ISC (local) and RASP (global), allows global influential and prioritize inter-community bridging nodes, as their removal significantly disrupts the network connectivity. Initially divide the group of nodes into clusters based on their similar characteristics. These characteristics are identified by using various community detection methods. In our study, we used Kumar's method to detect the communities in the hypergraph. Kumar's method is a modified version of the Louvain method on a 2-section graph by adjusting the edge weights according to the hypergraph structure and enables hyperedges distribution across communities [21]. Comparing to other community detection methods the Kumar's method directly works on hypergraph and adjusts the hyperedges based on the structure. To check the efficiency of the community detection method, we use hypergraph modularity. A high modularity score suggests that the nodes share many hyperedges within the same community.

For implementation, first we detect the communities by using Kumar's method, then compute centrality measures for each community, and the procedure is shown in algorithm 1. The count of communities is not fixed, and it is dynamically determined by Kumar's method. By Fig. 2, the next step is to identify the top ten nodes from the centrality measure. After ensuring one seed node from each community, the remaining seed nodes are allocated by focusing on large communities first and then selects the next high-ranked centrality node that has not been chosen before. By collecting these top ten seed nodes, we compare the efficiency of the proposed centrality with existing centralities for real-world datasets within the community structure is discussed in subsequent sections.

C. COMPUTATIONAL ANALYSIS OF TOY EXAMPLE

We analyze the computational complexity of the proposed community-based IRASP computation and use a toy hypergraph Fig. 1 to demonstrate its implications for ensuring computational efficiency. Traditional full-hypergraph computation of global centrality metrics like closeness and RASP requires repeated computation of the shortest paths across the entire hypergraph, making the computations increasingly expensive for large-scale networks. In contrast, the proposed method significantly reduces the effective problem size by restricting centrality computations within communities. Further, we compare centrality values obtained from both the full-hypergraph and community-based hypergraph for the toy example, as presented in Table. 2. Besides the proposed IRASP measure, conventional global and local centrality measures are also included: betweenness centrality (BC), closeness centrality (CC), degree centrality (DC),

TABLE 2. Centrality values for full hypergraph vs community-based hypergraph of Fig. 1.

vertex(v)	centrality values without community							centrality values with community						
	BC	CC	DC	HC	ISC	RASP	IRASP	BC	CC	DC	HC	ISC	RASP	IRASP
1	0.01	0.56	0.22	5.83	0.0	0.006	0.003	0.0	**1.0**	2.0	1.0	0.0	0.722	0.577
2	0.03	0.6	0.22	6.33	0.0	0.009	0.004	0.0	1.0	1.0	**2.0**	0.0	0.75	0.600
3	0.19	**0.75**	**0.33**	**7.83**	0.0	0.089	0.044	0.0	1.0	1.5	2.0	0.0	0.888	0.711
4	0.18	0.69	0.33	7.0	0.0	0.105	0.052	0.0	1.0	**3.0**	1.0	0.0	**0.916**	0.723
5	0.02	0.52	0.22	6.08	0.0	0.022	0.011	0.0	1.0	1.0	2.0	0.0	0.694	0.555
6	0.02	0.6	0.22	6.33	0.0	0.009	0.004	0.0	1.0	1.0	2.0	0.0	0.75	0.600
7	0.02	0.6	0.22	6.33	0.0	0.009	0.004	0.0	1.0	1.0	2.0	0.0	0.75	0.600
8	**0.22**	0.69	0.22	7.0	0.0	0.105	0.052	0.0	1.0	1.0	2.0	0.0	0.912	**0.733**
9	0.19	0.56	0.22	5.83	**0.2**	**0.196**	**0.098**	0.0	1.0	2.0	1.0	**1.0**	0.392	0.514
10	0.0	0.37	0.11	3.91	0.0	0.134	0.067	0.0	1.0	1.0	1.0	0.0	0.5	0.4

harmonic centrality (HC), isolating centrality (ISC), and relative average shortest path (RASP).

In a community-based computation framework of IRASP, exhibits considerable changes in centrality measures and their rankings compared with the full-hypergraph. This behavior suggests that computation based on community substructures affects the assessment of influence while preserving relative importance among key vertices. The obtained results justify that the proposed community-based IRASP framework captures both the local and global structural features better than any individual centrality measure.

To provide an intuitive understanding of the proposed IRASP measure, we explicitly calculate all centrality values using a toy hypergraph. Since IRASP is defined as a weighted combination of ISC and RASP, setting the parameter $\alpha = 0$ reduces IRASP to the global RASP measure, whereas setting $\alpha = 1$ yields the local isolating centrality. Intermediate values of α interpolate between local and global structural characteristics. We evaluate the IRASP measure on the toy hypergraph for different values of α. The resulting IRASP values for both the full hypergraph and the community-based hypergraph are shown in Table. 3. The results illustrate how IRASP adapts to different parameter settings while preserving the relative importance of influential nodes. The results demonstrate that the isolating component captures local structural importance, while the RASP component emphasizes global bridging roles. Their combination consistently outperforms the individual components across Kendall Tau correlation and SIR-based spreading efficiency, indicating a complementary effect.

D. TIME COMPLEXITY

Consider a hypergraph $H = (V, E)$, represented by edge-list, where |V| is n (number of nodes) and $|E|$ is m (number of hyperedges) and $\bar{k}$ is average size of hyperedge. The shortest path calculations in hypergraph performed by node hyperedge traversal and time complexity for centrality measures are shown in Table. 4. When the community-based approach is applied, the entire hypergraph is partitioned into communities C, and centrality measures are computed on corresponding communities. The computational cost of proposed IRASP combines both isolating centrality and RASP. The time complexity of isolating centrality (ISC) for all nodes is $O(m\bar{k}^2)$. ISC computes the isolation coefficient of its neighbor nodes by considering incident hyperedges and aggregates all these hyperedges to get the computational cost. The RASP time complexity is relying on the relative change in average shortest path when the node is removed. Computation of average shortest path requires all-pairs-shortest-path distances, which works under the edge-list model gives $O(n^2 m\bar{k})$) time, and this calculation repeated for each removed node n in each turn, the time complexity yields $O(n^2 m\bar{k})$). Proposed method IRASP is the combination of both ISC and RASP, the time complexity is $\max(O(m\bar{k}^2), O(n^3 m\bar{k}))$. Since the weighting parameter is constant, the computational constant of IRASP is dominated by the RASP component. By, restricting the computations to community-structured hypergraphs the time complexity is $\max\left(O\left(\frac{m\bar{k}^2}{C}\right), O\left(\frac{n^3 m\bar{k}}{C}\right)\right)$, and it reduces the problem size and improves scalability.

VI. IMPLEMENTATION

This section provides a detailed description of the datasets and evaluation metrics employed in our study. These evaluation metrics computes the efficiency of proposed method over existing centrality measures in terms of correlation and information dissemination within the network.

A. DATASETS DESCRIPTION

We implemented experiments on six different datasets to check the efficiency of our proposed centrality measure. In our work the hypergraphs is represented in edge-list format, then we divided the communities for each real-world dataset. In second step we calculated centrality values by using both existing centrality measures, and proposed centrality measure for each community. Then evaluated the efficiency of centrality measures over the communities in each dataset by using evaluation metrics Kendall Tau and diffusion model. The detailed description of the datasets is given below, and some basic properties is computed on datasets and the values are shown in Table. 5.

TABLE 3. IRASP values under different weighting parameters and comparing local-only, global-only and combined (hybrid) for the toy example on full-hypergraph vs community-based computation.

vertex (v)	For Full-hypergraph			For Community-based Hypergraph		
	$\alpha = 1$	$\alpha = 0$	$\alpha = 0.5$	$\alpha = 1$	$\alpha = 0$	$\alpha = 0.5$
1	0.0	0.006	0.003	0.0	0.722	0.577
2	0.0	0.009	0.004	0.0	0.75	0.600
3	0.0	0.089	0.044	0.0	0.888	0.711
4	0.0	0.105	0.052	0.0	**0.916**	0.723
5	0.0	0.022	0.011	0.0	0.694	0.555
6	0.0	0.009	0.004	0.0	0.75	0.600
7	0.0	0.009	0.004	0.0	0.75	0.600
8	0.0	0.105	0.052	0.0	0.912	**0.733**
9	**0.2**	**0.196**	**0.098**	**1.0**	0.392	0.514
10	0.0	0.134	0.067	0.0	0.5	0.4

TABLE 4. Time complexity comparison of hypergraph centrality measures using incidence list representation.

Centrality Measure	Without Communities	With Communities
Degree Centrality	$O(m\bar{k})$	$O(m\bar{k})$
Closeness Centrality	$O(nm\bar{k})$	$O\left(\frac{nm\bar{k}}{C}\right)$
Harmonic Centrality	$O(nm\bar{k})$	$O\left(\frac{nm\bar{k}}{C}\right)$
Betweenness Centrality	$O(nm\bar{k})$	$O\left(\frac{nm\bar{k}}{C}\right)$
ISC	$O(m\bar{k}^2)$	$O(m\bar{k}^2)$
RASP	$O(n^3m\bar{k})$	$O\left(\frac{n^3m\bar{k}}{C}\right)$
IRASP	$\max(O(m\bar{k}^2), O(n^3m\bar{k}))$	$\max\left(O\left(\frac{m\bar{k}^2}{C}\right), O\left(\frac{n^3m\bar{k}}{C}\right)\right)$

1) EMAIL-ENRON

It was designed based on the structure of email system used by people in Enron [40], [41]. The email that includes the multiple people, and uses a simplexes to represent these group interactions. The nodes are email addresses of employees in Enron and hyperedges are time steps where it includes sender and all recipients of an email.

2) SENATE-COMMITTEES

Dataset constructed from congressional data compiled by Charles Stewart and Jonathan Woon, where the nodes are US senates members and hyperedges are designed based on committee memberships [18], [41].

3) CONTACT-HIGH-SCHOOL

This dataset focuses on the group of people and their interactions at high school over time intervals. The data was collected from sensors worn by everyone in the school. For every 20 seconds, the sensors check the interaction of people with each other and save this as simplex. Then each node is a person and a hyperedge is a simplex that shows the group of people and their interactions in short time intervals [41], [42], [43].

4) CAT-EDGE-VEGAS-BARS-REVIEWS

This dataset was taken from the Yelp Kaggle competition data, where the nodes represent Yelp users and hyperedges are created by users who reviewed different types of bars in Las Vegas during a one-month period [41], [44].

5) HOUSE-COMMITTEES

In this dataset where nodes are members of the representatives of house and hyperedges are membership holders based

TABLE 5. Summary of datasets including number of nodes, hyperedges, diameter, maximum degree, and average degree.

Dataset	Nodes	Hyperedges	Diameter	Max. Deg.	Avg. Deg.
email-Enron	143	1514	4	118	32.33
senate-committees	282	315	3	375	19.18
contact-high-school	327	7818	4	148	55.63
cat-edge-vegas-bars-reviews	1234	1194	6	147	9.62
house-committees	580	1193	4	44	9.18
cat-edge-algebra-questions	420	1267	5	375	19.66

on the committee. The data is taken from the congressional data and nodes are labeled with political party affiliation [41].

6) CAT-EDGE-ALGEBRA-QUESTIONS

The dataset is created from Stack Exchange data dump and where nodes are users from MathOverflow and set of users who answered algebra questions are categorized to. hyperedges based on their tags involved in algebra [41].

Simulations on these datasets were evaluated on a PC powered by an Intel Core™i9-14900 CPU running at 3200MHz with 24 Cores, 32 logical processors, and 64GB of RAM. The community division of hypergraph, centrality measure evaluation with and without community, correlation analysis, and information propagation simulations are computed by using Anaconda software, specifically by using Jupyter Lab. The visualization plots in the result section were generated by using Origin Pro software.

B. KENDALL RANK CORRELATION COEFFICIENT

The Kendall's Tau rank correlation is a statistical measure that captures the association between two ranked variables [45], [46]. In our work, for assessing the efficiency of proposed method we used the Kendall's Tau rank correlation. Let R and T be two ranking lists, and a pair of (R_i, T_i) and (R_j, T_j) is concordant if $((R_i > R_j)$ and $(T_i > T_j))$ or $((R_i < R_j)$ and $(T_i < T_j))$ both rankings follow the same trend and the pair is discordant if $((R_i > R_j)$ and $(T_i < T_j))$ or $((R_i < R_j)$ and $(T_i > T_j))$. The Kendall's coefficient is computed by using Eq. 20

$$\tau = \frac{N_C - N_D}{\frac{1}{2}(n(n-1))}, \tag{20}$$

where n is each sample size, N_C is total number of concordant pairs, and N_D is total number of discordant pairs. If τ is equals to 1, it denotes a perfect match between two ranked lists. If τ equals to -1, it signifies that one ranking is completely reverse to other rankings.

C. INFORMATION SPREADING MODEL

In our work, we focus on the SIR diffusion model to investigate how top ranked nodes propagate information over the hypergraphs. For implementation process, we initially chosen the top ten infection nodes form each centrality measure [47]. The infection spreads to complex network based on SIR model by these ten infected nodes. With infection rate probability, the infection spreads to the susceptible nodes i.e, neighbor nodes of infected nodes. Infected nodes can recover with the probability of γ at every step, then the process continues until no infected nodes detected in hypergraph. Spreading ability is initially less, over the steps increases saturation also increases and at certain threshold the spreading infection decreases.We performed 100 iterations, by considering the transmission rate β varying from 0.01 to 0.4 for 40 time stamps [48]. In subsequent section, we evaluate the efficiency of proposed method by using these two metrics and applied on six distinct datasets.

D. PARAMETER SETTINGS

The proposed method combines local and global structural disruption through a convex combination of isolating centrality (ISC) and RASP, controlled by the weighting parameter $\alpha \in [0, 1]$. We fix $\alpha = 0.2$ as the baseline value and computed the IRASP rankings. To assess the sensitivity of IRASP with respect to the weighting parameter, we conduct a sensitivity analysis by varying $\alpha \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$. The similarity between the resulting node rankings at different α values is evaluated using Kendall's Tau correlation coefficient. The correlation values, reported in Table 6, are consistently high across all datasets, indicating that the node rankings remain highly stable under variations of α. Based on this evaluation, we fix $\alpha = 0.2$ as it provides a balanced emphasis on global structural effects while retaining sensitivity to local isolation captured by ISC. Furthermore, the results show that additional parameter tuning does not lead to meaningful changes in the node rankings.

For evaluating proposed method performance, the information spreading metric is essential to identify the spreading efficiency within the network. To observe this, we need the parameters β for infection rate and γ for recovery rate. The β value ranges from 0.01 to 0.4, which enables to check the performance of proposed centrality measures [47], [48]. The γ stands for recovery rate and it is fixed at 1, to ensure the infected node can be recovered once it transmits the infection to adjacent nodes. Based on the β value range, we observed the effectiveness of proposed method by simulating 100 iterations over 40 time steps. These chosen intervals of parameters improve our results and the impact is shown in Table 7. These parameters captures both low and high spreading points, when we are using various transmission rates. The β value is taken up to 0.4, because when the more number of nodes are infected at initial steps the spreading of information is remaining as constant at certain time step. Fixing γ, ensures a consistent recovery process, while changes in β value enables to observe difference in spreading dynamics, and network structure.

VII. RESULTS

In this section, we provide the simulation results to compare the proposed method with existing centrality measures in the literature. In evaluation process we first consider the correlation analysis between proposed and other centralities. After satisfying the correlation constraint then move to next step SIR diffusion model, to compute cumulative infected nodes for centralities. Finally, we compare existing and proposed centrality measures at various infection rates and captures the maximum total number of infected nodes for each dataset.

A. CORRELATION ANALYSIS BETWEEN BASIC AND PROPOSED CENTRALITY MEASURES ON COMMUNITIES IN HYPERGRAPHS

In this subsection, we discuss correlation analysis of hypergraph community structure for various centralities BC, CC, DC, HC, RASP and proposed centrality. The rank correlation is computed by evaluation metric Kendall Tau, across on six different datasets email-Enron, senate-committees, contact-high-school and cat-edge-vegas-bars-reviews. Initially we consider top 100 ranked nodes from each centrality measure and evaluated the correlation between the proposed centrality and existing centralities. In email-Enron dataset, IRASP has moderate correlation between DC and BC, and comparatively lower correlation with HC and CC. In senate-committees dataset, the RASP is highly correlated with IRASP and DC, CC shows moderate correlation with proposed centrality. While BC and HC shows weaker correlation as number of nodes increases the correlation also increases. As the proposed centrality IRASP has both local and global information, so IRASP is moderately correlating with existing centralities. Observe, contact-high-school dataset the correlation values are highly fluctuating at every stage. In overall datasets, RASP is highly correlated with proposed centrality IRASP. In cat-edge-vegas-bars-reviews dataset, shows lowest correlation values among all centralities compared to IRASP. Comparing to all datasets, the cat-edge-vegas-bars-reviews dataset shows less correlation. In house-committees dataset, shows the high correlation with proposed centrality IRASP. The cat-edge-algebra-questions dataset, shows less correlation with other existing centrality methods. By observing the Fig. 3, IRASP centrality is structurally most aligned with RASP, showing that the relative influence component in IRASP is dominant. We considered the communities from each dataset and collected 100 nodes of each centrality measure to compute correlation and also computed correlation for total nodes from each centrality measure for each dataset the correlation values are shown in Table. 8.

To assess the stability of IRASP rankings with respect to different community detection strategies, we compare rankings that are generated from Hy-MMSBM and h-Louvain with Kumar's method. For each dataset, IRASP values are computed separately under each community partitions, and the obtained node rankings are compared using Kendall's tau correlation. As shown in Table 9, the stability of rankings across both divisions are varies between datasets, which confirms that community structure shows affects on nodes and their relative importance. Rankings with higher tau values suggest strong interaction between the rankings produced from different community algorithms, lower tau values shows the node importance is sensitive to partitioning method. These results confirms that IRASP yields consistent ranking behaviour across different community detection methods and, at the same time, it remains sensitive to structural differences as captured by each algorithm. As IRASP combines isolating (local) and path-based (global) components through the weighting parameter α, variations in community structure only substantially alter the relative balance between local isolation and global connectivity, as expressed in ranking correlations.

B. ANALYSIS ON CUMULATIVE INFECTED NODES OF PROPOSED AND BASIC CENTRALITIES

In this subsection, we compute the cumulative infected nodes for various centrality measures using the SIR (Susceptible-Infected-Recovered) model applied on six different datasets: email-Enron, senate-committees, contact-high-school, and cat-edge-vegas-bars-reviews. Initially we consider top ten seed nodes, from each centrality measure of distinct datasets. By using SIR diffusion model, we first infect top ten seed nodes then in next step the neighbors of seed nodes are infected with probability transmission rate β. The infected nodes can be recovered at every step with the recovery rate γ. For experimentation we iterated 100 simulations over 40 time steps, resulted with average cumulative infected nodes. We performed the experimentation process on six different datasets, and the plots are shown in Fig. 4. All centralities in email-Enron dataset performs slightly faster and shown higher infection saturation. In senate-committees dataset, high saturation occurred at initial time steps, further the proposed IRASP consistently shown superiority in cumulative infection comparing with other existing centrality measures. The house-committees dataset, performs faster saturation at starting level, but our proposed method shows more cumulative infected nodes compare to existing methods. In cat-edge-algebra-questions datasets, the existing methods and IRASP spreads the information rapidly to all the nodes in network, but as cumulative infection the IRASP shows slightly high saturation than existing methods. Proposed centrality IRASP achieves faster and higher infection saturation than other centrality measures in contact-high-school dataset. Similarly in cat-edge-vegas-bars-reviews captures a more extensive spread over time steps.

Across all datasets, proposed IRASP centrality consistently spreads the information faster in the SIR model compared to classical centrality measures within the range

TABLE 6. Sensitivity analysis of IRASP node rankings with corresponding weighting parameters α, quantified by using Kendall's τ correlation.

Dataset	$\alpha = 0.2$ vs 0.1	$\alpha = 0.2$ vs 0.3	$\alpha = 0.2$ vs 0.4	$\alpha = 0.2$ vs 0.5
email-Enron	0.92	1.00	1.00	1.00
senate-committees	0.99	1.00	1.00	1.00
contact-high-school	1.00	1.00	1.00	1.00
cat-edge-vegas-bars-reviews	1.00	1.00	1.00	1.00

TABLE 7. SIR model parameter settings and their impact on spreading dynamics.

Parameters	Range	Explanation	Influence on Spreading Dynamics
β	0.01 – 0.4	Captures both low and high spreading dynamics.	Controls the infection spread: low values leads to slow infection spreading and high values leads to rapid infection spreading.
γ	1 (fixed)	Maintains a recovery timescale.	Maintains uniform recovery dynamics, and allows reliable comparisons across different networks.

TABLE 8. Kendall Tau correlation between IRASP and other centrality measures across different datasets.

Datasets	$\tau(\mathbf{DC}, \mathbf{IRASP})$	$\tau(\mathbf{BC}, \mathbf{IRASP})$	$\tau(\mathbf{CC}, \mathbf{IRASP})$	$\tau(\mathbf{HC}, \mathbf{IRASP})$	$\tau(\mathbf{RASP}, \mathbf{IRASP})$
email-Enron	0.89343	0.87708	0.80144	0.82350	0.96612
senate-committees	0.87577	0.74190	0.85498	0.55014	0.73267
contact-high-school	0.90510	0.88946	0.91655	0.90983	0.55337
cat-edge-vegas-bars-reviews	0.81958	0.85929	0.85929	0.82569	0.82569

TABLE 9. Kendall's tau correlation using IRASP node rankings between Kumar's method with other methods (Hy-MMSBM, h-louvain) community detection across different datasets.

Dataset	$\tau(\mathbf{Kumar's}, \mathbf{Hy-MMSBM})$	$\tau(\mathbf{Kumar's}, \mathbf{h-louvain})$
email-Enron	0.5921	0.2654
senate-committees	0.1569	0.6309
contact-high-school	0.0142	0.6254
cat-edge-vegas-bars-reviews	0.0155	0.8618

of 0.002% to 0.05%. The improvement in diffusion analysis shows moderate in some cases, such variations are common in influence diffusion because many centrality measures generally identify a similar set of highly influential nodes. The small improvements of identifying influential nodes can lead to significant variations in the entire diffusion process, specifically in large scale networks. The IRASP demonstrates robust performance across datasets that integrates structural isolation and path based influence allows a more balanced computation of node importance in hypergraphs. This shows the IRASP ability to capture influential nodes in hypergraph datasets more effectively comparing with other centrality measures.

C. MAXIMUM INFORMATION SPREAD VARIES FROM TRANSMISSION RATES

In order to understand the effects of varying spreading probabilities, we examine the maximum number of infected nodes with different transmission rates in this subsection. The top 10 seed nodes are considered as infected nodes then the transmission probability ranges from 0.01 to 0.4 to investigate the infection's spread. We choose top five beta values from the transmission probability range to check the affect of infection spread within the network. The maximum number of infected nodes across the six datasets displayed in Table. 10. In email-Enron dataset, the transmission rate remains relatively constant across RASP and BC. In contact-high-school, IRASP shows superior performance on highest infection count across almost all transmission rates. In cat-edge-vegas-bars-reviews IRASP perform closely with all centrality measures. Across different datasets, the IRASP consistently identifies maximum number of infected nodes at each transmission rate. The house-committees dataset the saturation is rapid, we varied for different transmission rates and captured the maximum infected nodes for all centrality measures. In cat-edge-algebra-questions the maximum infected nodes are observed for all centrality measures, the proposed

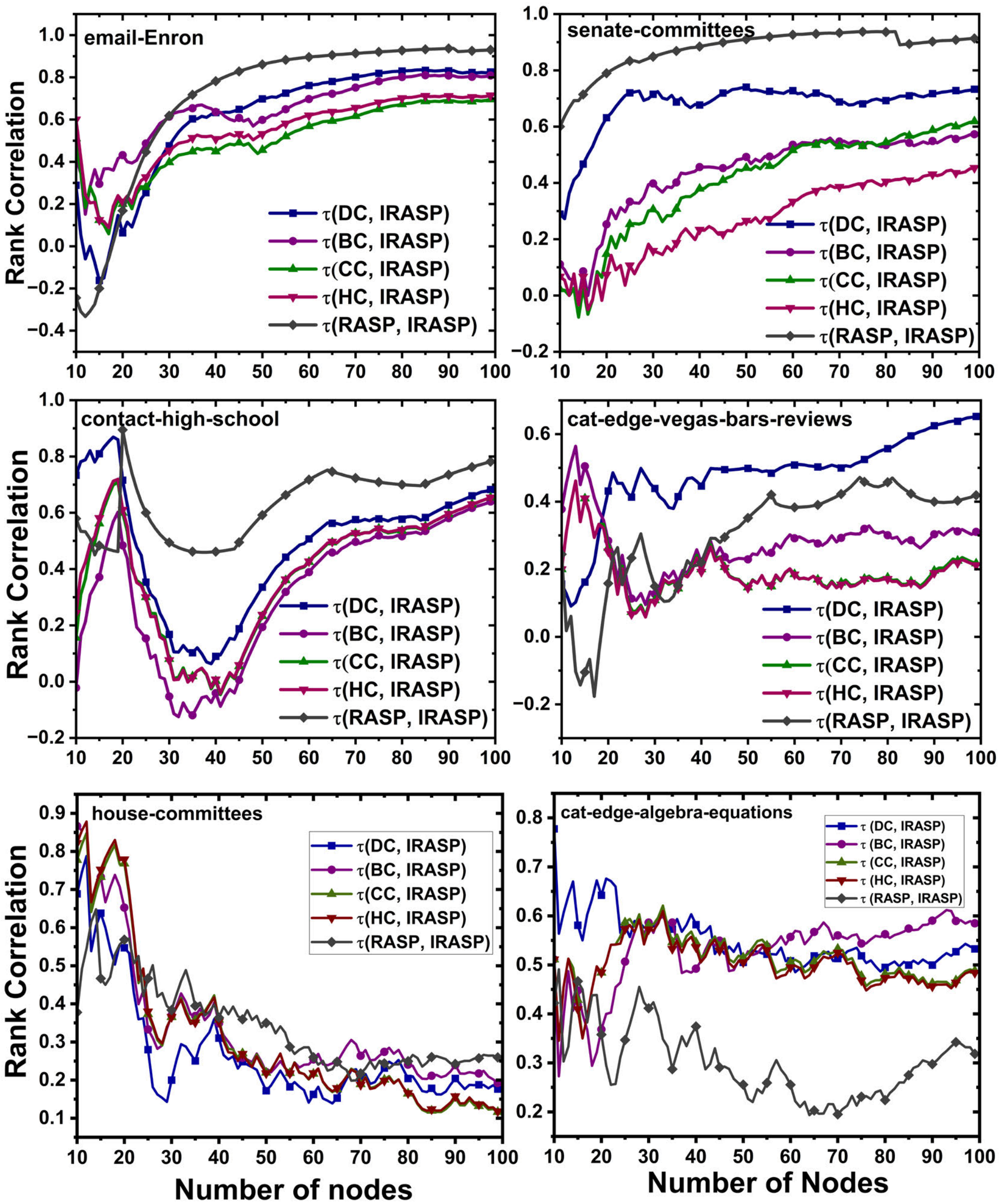

FIGURE 3. Correlation Analysis between different centrality measures (BC, CC, DC, HC, RASP) and proposed centrality measure (IRASP) for community structured hypergraph.

centrality IRASP shows the slight higher value than existing methods. To enhance the evaluation, the IRASP is compared with recent centrality methods such as LED and NDC, which captures extended neighborhood structure within the datasets. The results demonstrate the IRASP consistently shown higher performance with recent measures across different datasets. IRASP validates a robust and adaptable technique for modeling information propagation under different diffusion conditions.

D. ANALYSIS ON INFORMATION PROPAGATION OVER WITH COMMUNITY AND WITHOUT COMMUNITY

In this subsection, we used the SIR diffusion model to analyze the spread of information and compared centrality metrics on four distinct datasets with and without communities. Apply community detection to a hypergraph, and then calculate centrality measures for each community. In community structured hypergraph the centrality measures are named as community-based betweenness centrality (CBC), community-based closeness centrality (CCC), community-based degree centrality (CDC), community based harmonic centrality (CHC), community-based relative average shortest path (CRASP), and community-based isolating relative average shortest path (CIRASP). Observe Fig. 5, where we compared the information propagation of each centrality measure for the general hypergraph and the community, on four distinct datasets email-Enron, senate-committees, contact-high-school, and cat-edge-vegas-bars-reviews. The

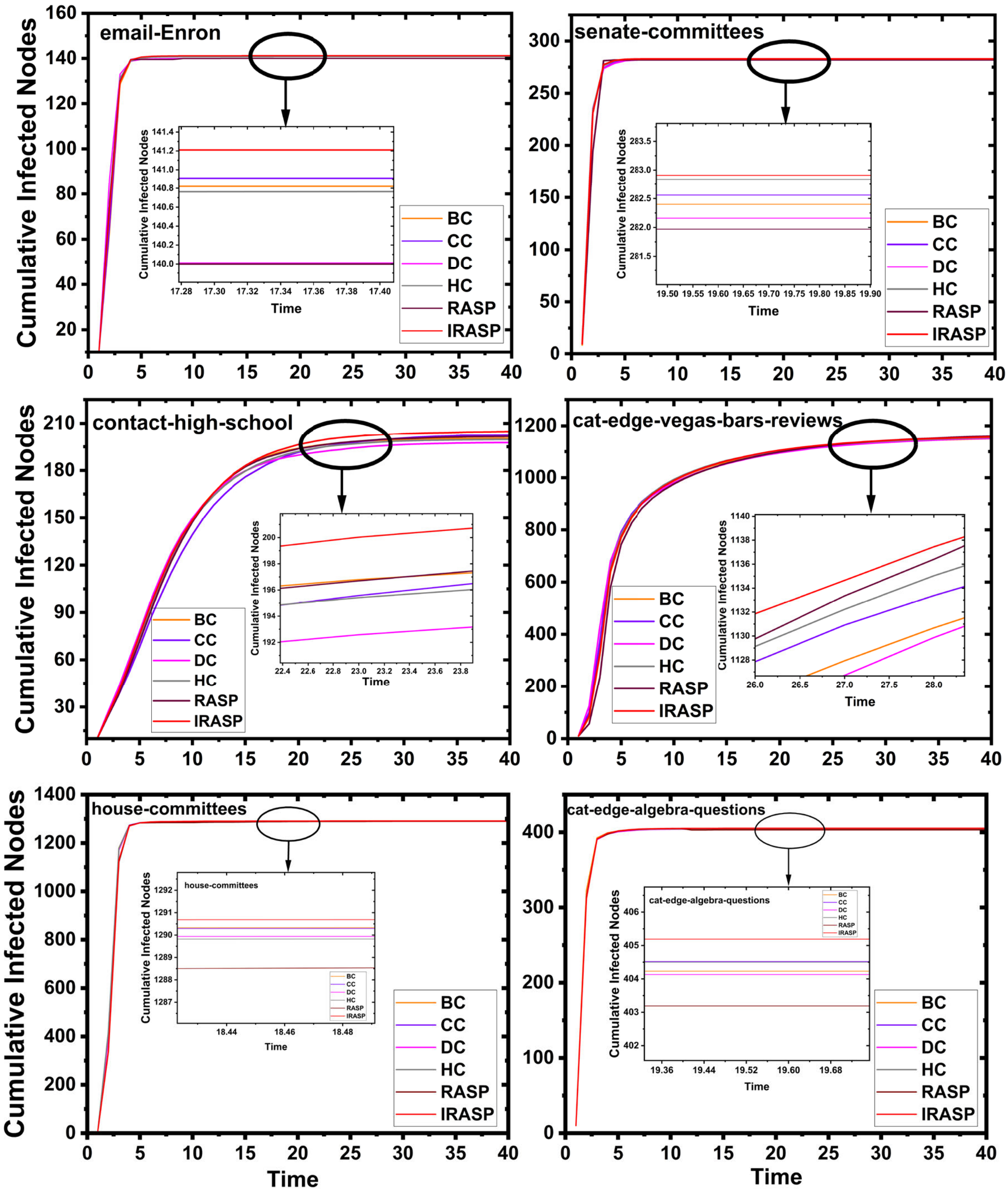

FIGURE 4. Cumulative infected nodes based on the SIR model, evaluated over 100 simulations across 40 time steps, for the six real-world hypergraph datasets email-Enron, senate-committees, contact-high-school, and cat-edge-vegas-bars-review, house-committees, and cat-edge-algebra-questions.

Fig. 5 compares the cumulative number of infected nodes between centrality measures and community-based centrality measures. Both community-based betweenness centrality (CBC) and betweenness centrality (BC) achieve comparable spreading across all datasets. However, CBC consistently exhibits a slight difference by reaching a greater number of infected nodes ranging form 4.9% to 0.07%. Both closeness centrality (CC) and community-based closeness centrality (CCC), exhibit fast initial infection growth followed by saturation across all datasets, but it spreads more quickly with higher infection count. The inset plots demonstrate these subtle and show consistent benefits, with CCC exhibiting a noticeably faster spread in cat-edge-vegas-bars-reviews and a slightly higher influence in datasets such as email-Enron

TABLE 10. Maximum information spread varies at different transmission rates for each centrality measure on six distinct real-world hypergraph datasets.

Dataset	β	BC	CC	DC	HC	RASP	ND	LED	IRASP
email-Enron	0.03	141.54	141.82	141.15	141.94	141.56	134.77	135.88	141.92
	0.04	138.50	138.56	137.16	138.59	138.50	136.70	136.78	138.48
	0.06	139.92	139.98	138.81	140.37	139.92	138.70	138.72	140.26
	0.08	140.82	140.92	140.01	140.77	141.00	139.61	139.83	141.21
	0.09	142.81	142.85	142.71	142.89	142.66	139.93	140.11	142.77
senate-committees	0.01	282.47	282.60	282.23	282.99	281.95	282.23	282.13	283.01
	0.04	282.32	282.54	282.28	282.72	281.95	281.81	282.11	282.82
	0.05	282.40	282.56	282.16	282.84	281.97	281.33	282.52	282.91
	0.06	282.34	282.26	282.13	282.87	281.94	281.11	282.33	282.79
	0.07	282.36	282.47	282.32	282.57	281.92	282.52	281.72	282.73
contact-high-school	0.01	200.43	202.76	197.72	199.66	201.70	195.83	187.43	204.92
	0.02	320.41	320.20	320.58	320.29	320.24	247.04	249.23	320.79
	0.06	306.04	305.40	306.24	305.94	306.06	305.98	306.01	306.60
	0.07	323.27	323.42	323.45	323.51	323.40	310.41	310.44	323.58
	0.08	313.85	313.10	313.40	313.96	313.67	313.97	313.93	314.37
cat-edge-vegas-bars-reviews	0.01	1155.74	1151.30	1152.00	1154.65	1155.28	1150.29	1152.65	1156.90
	0.05	1221.57	1221.90	1221.13	1221.84	1221.12	1221.03	1221.23	1222.02
	0.06	1222.53	1221.88	1222.88	1222.61	1221.76	1222.27	1222.38	1223.07
	0.11	1224.12	1224.20	1224.26	1224.30	1223.50	1223.93	1224.12	1224.55
	0.15	1224.53	1224.42	1224.55	1224.50	1224.45	1224.48	1224.52	1224.60
house-committees	0.04	1290.54	1290.61	1290.14	1290.16	1289.99	1289.15	1289.34	1290.99
	0.05	1289.72	1290.08	1289.17	1289.75	1289.56	1289.08	1289.23	1290.24
	0.06	1289.55	1289.28	1288.88	1289.64	1289.46	1288.52	1289.02	1290.02
	0.07	1289.13	1289.06	1288.86	1289.37	1289.32	1288.49	1289.12	1289.52
	0.08	1289.01	1288.93	1288.61	1289.31	1288.36	1288.35	1289.08	1289.43
cat-edge-algebra-questions	0.05	404.23	404.52	404.13	404.5	404.4	403.99	404.02	405.19
	0.06	404.23	404.32	404.05	403.99	404.4	403.52	403.89	405.17
	0.09	404.23	404.32	404.05	403.99	404.4	403.52	403.89	405.16
	0.11	404.11	404.02	404.00	403.76	404.2	403.36	403.82	405.08
	0.12	404.08	404.02	403.99	403.76	404.2	403.02	403.80	404.89

and senate-committees, the overall information spreading of CCC ranges from 0.9% to 0.1%.

Across four datasets, the degree centrality (DC) and community-based degree centrality (CDC) spreads rapid infection. However, CDC consistently achieves the high infection rate and faster convergence compared with DC. The zoomed plot highlights the final stages of diffusion. In email-Enron and contact-high-school datasets, CDC achieves a higher infection count and saturates infection faster than DC over the time. By observing the Fig. 5, states that CDC leads to better diffusion than traditional DC with the percentage of 2.3% to 0.07%. The harmonic and community-based harmonic centrality (CHC), show a rapid rise in infection and reach saturation phase in early timestamps. However, CHC consistently outperforms the HC as shown in zoomed plots in Fig. 5. Observe the plots of HC, the CHC reaches a higher number of infected nodes and indicates a slightly more effective influence spread when community structure

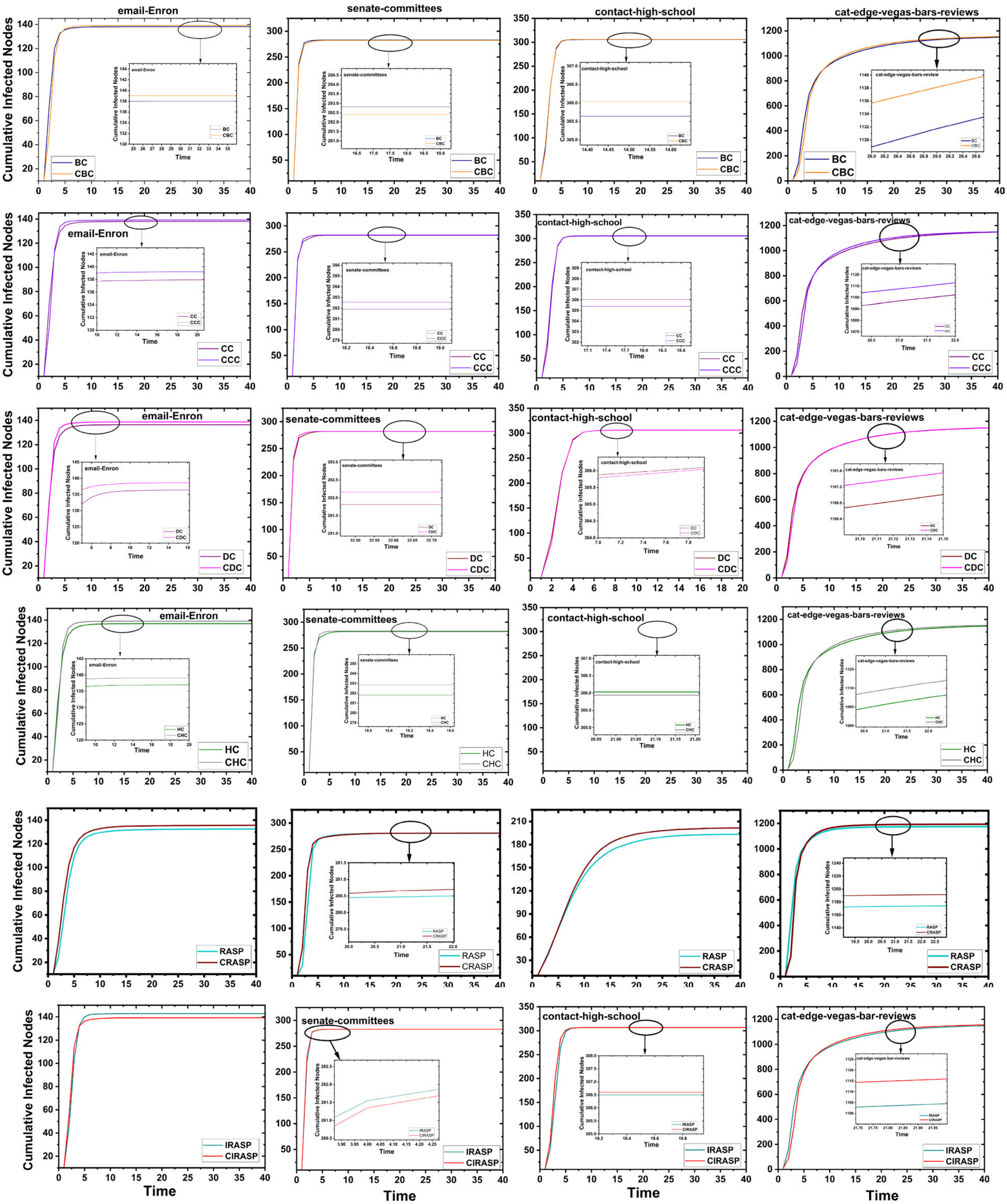

FIGURE 5. Comparison of information diffusion over time using traditional centrality measures (BC, CC, DC, HC, RASP, IRASP) and community-based centrality measures (CBC, CCC, CDC, CHC, CRASP, CIRASP) across four real-world hypergraph datasets.

integrated with harmonic centrality. CHC shows subtle but consistent improvements within the range of 2.4% to 0.3% in diffusion over HC.

Community-based relative average shortest path (CRASP) consistently outperforms relative average shortest path (RASP) by achieving higher cumulative infections. The advantage is more clear in the senate-committees and cat-edge-vegas-bars-reviews datasets, but CRASP still has lead in all time stamps with the range of 4.2% to 0.1%. Adding community structure to RASP makes diffusion more efficient

TABLE 11. Computational time (in seconds) for finding top ten seed nodes of RASP and IRASP centrality measures within the community and without community detection across four real-world hypergraph datasets.

Dataset	Without Community		With Community	
	RASP	IRASP	RASP	IRASP
email-Enron	65.11	69.22	17.37	18.40
senate-committees	1814.50	704.78	336.58	326.32
contact-high-school	965.33	881.07	254.84	166.16
cat-edge-vegas-bars-review	146289.00	140455.00	70447.30	61190.50

overall CRASP is better to spread influence in a hypergraph. Community-based isolating relative average shortest path (CIRASP) consistently outperforms its baseline isolating relative average shortest path (IRASP) within the percentage of 0.7% to 0.01% across all datasets by achieving higher cumulative infections and faster diffusion, as shown in the Fig. 5. CIRASP shows a significant improvement compared to other enhanced methods such as CRASP, CHC, and CCC, particularly on significant complex networks like senate-committees and contact-high-school. All of the community-based versions (CBC, CCC, CHC, CRASP, CIRASP) are better than their base centralities, however CIRASP is strongest in influence spreading capability by integrating community structure. The result indicates that CIRASP is the most effective approach to determine the maximum diffusion in hypergraphs.

Across the four datasets, community-based centrality measures consistently demonstrated the improved spreading performance compared to baseline methods. In senate-committees and cat-edge-vegas-bar-reviews, where the community structures capture the structural relationships of the hypergraph. Further, the datasets with dense interactions adapts the margin improvement compared to datasets with heterogeneous connectivity structures. The CIRASP shows significant cumulative infection and faster information spreading among these dataset variations compared to other existing measures in community structures.

E. COMPUTATIONAL ANALYSIS OF RASP AND IRASP: WITH COMMUNITY VERSUS WITHOUT COMMUNITY

In the following discussion, we analyses the computational time for finding seed nodes across four real-world datasets. In this simulation the main focus is on RASP and proposed centrality IRASP, first consider the four datasets then compute the computation time for overall hypergraph and communities in hypergraph. In this analysis, centrality measures on communities were executed using a parallel framework. Initially to evaluate the overall computation time, we considered two key points: (i) the time taken to perform community detection (dividing the network into communities), and (ii) the maximum time taken among all individual communities to identify their respective top seed nodes. By adding these two components, we obtain a total computation time in seconds for community-based centrality measures RASP and IRASP. The computational time of RASP and IRASP centrality measures, both with and without community detection, is shown in Table. 11 for four real-world datasets. We observe that, particularly in larger datasets such as cat-edge-vegas-bars-reviews, adding community structure considerably lowers the spread for both centrality measures in hypergraph. In the absence of community detection, RASP usually achieves a wider spread, whereas IRASP offers a more reliable and well-rounded performance. Notably, even after community integration, IRASP marginally outperforms RASP in the email-Enron dataset.

These results demonstrate how well community detection in centrality measures works to moderate and regulate the spread of information in intricate hypergraphs and achieve the less computation time than applying centrality measures directly on hypergraphs. Applying community detection on hypergraphs significantly reduced the computational time and gained efficiency from 65% to 81% for both RASP and IRASP centrality measures This resembles that working on communities for large-scale hypergraphs gives the less computation time and better information spreading than working directly on hypergraph. The combination of community detection and hypergraph structure enhances the scalability, reliability in information dissemination and reduction in computational cost.

F. LIMITATIONS OF IRASP

While the IRASP achieves a strong performance across different hypergraph datasets, it has certain limitations that are influence on specific characteristics such as hyperedge size, sparsity, and community structure.

(1) IRASP underperform in highly sparse or weakly disconnected hypergraphs, where it consists of disconnected components. In RASP computation these hypergraph connections are ignored, and it affects the IRASP and reduces it to local measure.

(2) In communities, IRASP ranking of the nodes depends on the quality of the community detection method. The over fragmented communities can reduce the global bridging between the nodes and weaken the local isolation patterns.

(3) In IRASP, the path-based information is captured by RASP component, when the hypergraph contains large hyperedges, then the shortest path distances are less discriminative and structural difference between the nodes becomes similar.

VIII. CONCLUSION AND FUTURE WORK

This study introduces a new centrality metric for hypergraphs, termed as Isolating Relative Average Shortest Path (IRASP), and integrates it with community detection to improve the identification of influential nodes. Centrality values are computed for each detected community across six real-world hypergraph datasets to evaluate the effectiveness of the proposed approach in terms of information propagation. Additionally, we computed the execution time of identifying seed nodes for community structure hypergraph and overall hypergraph of two centrality measures RASP and IRASP. These results demonstrate that integrating community structure into hypergraph, significantly improves both efficiency and performance of information spreading. Our proposed metric IRASP, outperforms various centrality measures such as BC, CC, DC, HC, RASP in both community structure hypergraph and overall hypergraph. The evaluated findings consistently demonstrating that our proposed metric on community structures in hypergraphs shown better performance in identifying key nodes ranging from 0.002% to 0.05% in information spreading. Although the improvements in information spreading are numerically small, this behavior is common in influence detection problems where the baseline measures exhibit strong saturation performance. These improvements are achieved by conducting SIR simulation over 100 iterations and 40 time steps. The improvement reflects small, but seed selection node rankings, which are evaluated across repeated diffusion processes with different parameters, lead to reliable identification of influential nodes. Moreover, it achieves superior performance compared to existing centrality measures across all datasets. In practical applications such as viral marketing and epidemic control, even the marginal improvements in information spreading can highly impacts in real-world scenarios.

The proposed centrality measure is versatile and can be extended to weighted and temporal hypergraphs. For weighted hypergraphs, weights can be assigned to hyperedges to represent interaction strength, with shortest paths redefined as the sum of traversed weights. For temporal hypergraphs, centrality can be calculated over time-sliced snapshots or time-respecting paths to identify influential nodes within evolving group dynamics. However, the framework has notable limitations. In hypergraphs with very large hyperedges, distance-based measures may overestimate node influence due to dense group interactions, potentially reducing the model's ability to discriminate between individual nodes. Additionally, calculating shortest paths is computationally expensive for large-scale or streaming hypergraphs, as frequent updates require partial or full recomputation. Improving scalability for dynamic environments remains a primary focus for future work.

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